Artificial Intelligence Based Food Quality Detection System

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by

Kashish Goyal
(Reg No: 901803018)

Under the supervision of

Dr. Parteek Kumar
and
Dr. Karun Verma

THAPAR INSTITUTE
OF ENGINEERING & TECHNOLOGY
(Deemed to be University)

Thapar Institute of Engineering and Technology
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List of Abbreviations

AI	Artificial Intelligence
ALP	Alkaline Phosphatase
ANN	Artificial Neural Network
APAM	Adaptive Pooling Attention Mechanism
AUC	Area Under Curve
BPNN	Backprogation Neural Network
BPNN	Back Propagation Neural Network
BRISQUE	Blind/Referenceless Image Spatial Quality Evaluator
CCD	Charge-Coupled Device
CDC	Centre for Disease Control
CM	Confusion Matrix
CNN	Convolution Neural Network
CSPNet	Cross-Stage Partial Network
CV	Computer Vision
DCGAN	Deep Convolutional Generative Adversarial Network
DCNN	Deep Convolution Neural Network
DL	Deep Learning
DNN	Deep Neural Network
DT	Decision Tree
E-Nose	electronic nose
E-Tongue	Electronic Tongue
EC	Electrical Conductivity
ELM	Extreme Learning Machine
EPA	Environmental Protection Agency

FCN	Fully Convolutional Network
FCN	Fully Convolutional Network
FDA	Food and Drug Administration
FDA	Fisher’s Discriminant Analysis
FDA	Fisher’s Discriminant Analysis
FN	False Negative
FP	False Positive
FPN	Feature Pyramid Network
FPR	False Positive Rate
FSIS	Food Safety and Inspection Service
FSSAI	Food Safety and Standards Authority of India
FTC	Federal Trade Commission
FTIR	Fourier Transform Infrared
GBM	Gradient Boosting Method
GLCM	Gray-Level Cooccurrence Matrix
GLRM	Generalised Low Rank Model
HCA	Hierarchical Cluster Analysis
HCA	Hierarchical Cluster Analysis
HCL	Hydrochloric acid
ICA	Independent Component Correlation Algorithm
IIT	Indian Institute of Technology
IoT	Information of Technology
IoU	Intersection over Union
KNN	K Nearest Neighbour
LBP	Local binary Pattern

LDA	Linear Discriminant Analysis
LED	Light Emitting Diode
LIF	Laser-Induced Fluorescence
LSN	Local Similarity Numbers
LSP	Local Similarity Patterns
MAE	Mean Absolute Error
mAP	Mean Average Precision
ML	Machine Learning
MLP	Multiple Layer Perceptron
MSE	Mean Square Error
NB	Naïve Bayes
NDRI	National Dairy Research Institute
NIR	Near Infrared
P	Precision
PANet	Path Aggregation Network
PCA	Principal Component Analysis
PCR	Principal Component Regression
PCR	Principal Component Regression
pH	Potential of Hydrogen
PhD	Philosophy of Doctorate
PLS	Partial Least Square
PLS	Partial Least Square
PLS-DA	Partial Least Square Discriminant Analysis
PLSM	Partial Least Square Method
PLSR	Partial Least Square Regression

PLSR	Partial least squares regression
QDA	Quadratic Discriminant Analsyis
R	Recall
RBF	Radial Basis Function
RBFNN	Radial Basis Function Neural Network
RBG	Red Blue Green
RCNN	Region Based Convolutional Neural Network
RF	Random Forest
RFID	Radio Frequency Identification
RFR	Random Forest Regression
RMSE	Root Mean Square Error
ROC	Receiver Operating Characteristic
RQ	Research Question
SFFS	Sequential Forward Floating Selection
SHAP	SHapley Additive exPlanations
SI	Separability Index
SNF	Solid Not Fat
SPVS	Single Plurality Voting System
SVM	Support Vector Machine
SVR	Support Vector Regression
TN	True Negative
TP	True Positive
TPR	True Positive Rate
VOC	Volatile Organic Compounds
WT	Wavelet Transform

XAI	Explainable Artificial Intelligence
YOLO	You Look Only Once

Certificate

I hereby certify that the work which is being submitted in this thesis entitled "Artificial Intelligence Based Food Quality Detection System" in the fulfillment of the requirements for the award of degree of DOCTOR OF PHILOSOPHY submitted in the Department of Computer Science and Engineering, Thapar Institute of Engineering and Technology, Patiala is an authentic record of my own work carried under the supervision of Dr. Parteek Kumar and Dr. Karun Verma, refers work of other researchers which are duly listed in the reference section. The matter presented in the thesis has not been submitted for the award of degree in any other University.

Kashish Goyal.
(Kashish Goyal)
Reg.No. 901803018

This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge and belief.

Parteek Kumar
(Parteek Kumar)
Professor, Computer Science and Engineering Department
Thapar Institute of Engineering and Technology, Patiala-147004 (INDIA)

(Karun Verma)
Associate Professor, Computer Science and Engineering Department
Thapar Institute of Engineering and Technology, Patiala-147004 (INDIA)

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Kashish Goyal.

(Kashish Goyal)

Abstract

In recent years, the modern food industry has been increasingly driven by consumer preferences for fresh, nutritious, and uncontaminated products, particularly in the case of fruits and milk. Ensuring food safety and quality is paramount, and to meet these demands, advanced technologies for quality detection have emerged. This research presents an innovative integrated system that harnesses the potential of artificial intelligence (AI), sensor technologies, and image analysis techniques to provide an efficient and reliable solution for food quality detection. AI algorithms can be trained to recognize patterns and anomalies in the sensory and image data collected from the food products. The integrated system addresses the limitations of conventional quality detection methods. Traditional methods often involve time-consuming and labor-intensive processes, making them less practical for real-time monitoring and assessment. In contrast, the AI-driven integrated system offers real-time and accurate assessments, significantly improving efficiency and reducing the time required for quality evaluation. This advancement is crucial in minimizing the risk of foodborne illnesses by promptly identifying potential hazards and ensuring compliance with safety standards.

Sensor technologies further enhance the system's capabilities by collecting vital data on various parameters like temperature, moisture, pH levels, and chemical composition. These sensors provide crucial insights into the freshness and overall quality of the food products. Image analysis techniques, integrated into the system, contribute to assessing visual attributes such as color, texture, and visual defects. By merging AI, sensor technologies, and image analysis techniques into an integrated system, the food industry can achieve a comprehensive and efficient approach to quality detection. This innovation has the potential to revolutionize food safety practices, reduce food wastage, and ultimately meet the growing consumer demand for high-quality, safe, and nutritious food products. Fruits and dairy products are essential components of a balanced diet for most living beings, including humans, due to their nutritional content and health benefits as it contains necessary vitamins and minerals.

Detecting fruit quality amidst complex backgrounds using an automated system holds paramount importance in the fruit industry. Among the critical factors in fruit grading, appearance plays a vital role, influencing market value and consumer preferences. However, there is a pressing need for an automated system to swiftly evaluate fruits, identify defects, and sort them based on their quality. Deep learning algorithms have revolutionized object

detection, making a substantial impact on fruit quality detection. Notably, Mask R-CNN and YOLOv5 are two prominent object detection algorithms that have been thoroughly experimented with in this study. YOLOv5 particularly stands out, showcasing superior performance, especially in scenarios requiring real-time object detection. The proposed work focuses on developing a fruit identification and quality detection model based on the YOLOv5 object detection system. The dataset encompasses images of four distinct fruits—apple, banana, orange, and tomato—categorized based on their ripening index. The model operates in two fundamental phases: first, fruit identification is accomplished, followed by fruit quality detection. Mosaic augmentation, a technique applied during the training of phase 1, significantly enhances detection performance and robustness of the system. The model accurately classifies the fruit, and the predicted image is subsequently forwarded to phase 2 for precise fruit quality detection. Results demonstrate that the proposed method effectively identifies fruits and detects their quality using the validation dataset. Real-time performance tests have been conducted using sample inputs to showcase the system's efficiency. The fruit identification and quality detection model have been compared with several state-of-the-art detection methods, yielding highly encouraging results, solidifying its potential and effectiveness in the realm of fruit quality assessment.

Additionally, most perishable fruit of the collected dataset tomato is further explored to evaluate shelf life of the fruit based on its ripeness index. A dedicated tomato quality detection system is introduced, focusing on analyzing specific attributes to ensure precise quality evaluation. It talks about an ensemble strategy to create a predictive system for tomato ripeness and shelf life, focusing on defects and color intensity. To ensure distinctiveness in the ensemble part of the proposed technique, a variety of expert base regressors, such as SVM, DT, RF, and GBM, are employed. Manual extraction of color, texture, and shape features is conducted, while the Inception V3 model automates feature extraction, subsequently reduced using the PCA dimensionality reduction method. The resulting ripeness regression models yield outputs categorized into three classes based on ripeness index and color magnitude, determining the tomatoes' shelf life as *Store, Sell, or Discount.* The stacking method is applied to consolidate these outcomes and produce the final prediction for the tomatoes' shelf life. The study reveals that incorporating different features, employing diverse pre-processing techniques, and utilizing skilled machine learning regressors significantly introduce variation into the ensemble approach, ultimately boosting accuracy compared to traditional machine learning models.

Further, the research explores dairy products besides fruits to evaluate milk quality. The milk quality evaluation is a vital process that entails a comprehensive assessment of various attributes and components to ascertain the overall quality and safety of milk. Addressing the pressing concern of milk adulteration, which poses significant threats to the nutritional value of milk and the well-being of consumers, this research introduces a novel AI-powered Internet of Things (IoT) integrated multi-sensor system.

The proposed system seamlessly integrates a range of sensors capable of real-time measurement, encompassing parameters such as pH, electrical conductivity (EC), temperature, gas properties, and Volatile Organic Compounds (VOC) parameters. This comprehensive approach extends to the measurement of crucial constituents within milk samples, including Fat, Protein, Solids Not Fat (SNF), Lactose, and Gravity values. To effectively identify specific adulterants—Urea, Starch, Sodium Bicarbonate, Maltodextrin, and Formaldehyde—a machine learning-based ensemble technique is employed for classification. This ensemble method surpasses conventional algorithms like RF, Light GBM, and Extra Trees Classifiers, achieving a notable accuracy rate in identifying adulterants present in the milk dataset. A significant aspect of this study is the creation of an IoT-based data acquisition device that seamlessly integrates with the sensor system, facilitating precise and efficient measurements. Additionally, SHAP (SHapley Additive exPlanations) analysis is utilized to elucidate the decision-making process of the ensemble model, thereby enhancing result interpretability. The system's ability to rapidly detect and categorize adulterants underscores its importance in mitigating the pervasive issue of compromised milk quality, thus ensuring consumer safety and upholding industry integrity. By integrating data from both fruit and milk quality detection modules, the system provides a comprehensive assessment of overall food quality. Leveraging the capabilities of AI and IoT, valuable insights are provided to producers, distributors, and consumers, empowering them to make informed decisions about food product freshness and safety. Extensive experiments using diverse datasets of fruits and milk samples validate the system's effectiveness, demonstrating high accuracy in detecting quality attributes and identifying potential risks associated with perishable food products. This pioneering research opens new avenues for leveraging AI and IoT technologies, paving the way for smarter, more efficient, and safer food supply chains, ultimately benefiting both producers and consumers alike. By ensuring consistent delivery of high-quality, untainted products, the integrated system aligns with consumer demands for wholesome and safe food options, while also contributing to elevated food safety standards and reduced economic losses due to spoilage and waste.

Chapter 1

Introduction to Food Quality

Food serves as the fundamental source of energy for all living organisms, playing a pivotal role in their growth and survival on Earth. The quality of food is crucial for assimilating essential nutrients necessary for comprehensive body development. As societies become increasingly interconnected, ensuring global food quality inspection and guaranteeing consumer safety have become imperative tasks. Rigorous food quality inspection processes are essential to identify and eliminate potential hazards such as contaminants, pathogens, or adulterants that could compromise the safety of the food supply chain. Governments, regulatory bodies, and international organizations collaborate to establish and enforce standards, protocols, and regulations to ensure the safety and quality of food products worldwide. Advancements in technology, including traceability systems, have enhanced the precision and efficiency of food quality inspections [1]. Continuous monitoring and global cooperation contribute to swift identification and containment of potential risks, preventing widespread outbreaks and safeguarding public health. The assurance of high-quality food through comprehensive global food quality inspection measures is vital to meeting the nutritional needs of a growing global population while safeguarding consumer safety and well-being.

Within this chapter lies a comprehensive overview of the thesis work. It explores a spectrum of factors that impact food quality, delves into the roles of federal agencies dedicated to food safety, and outlines general methods for detecting food quality. Additionally, it underscores the need for an automated system to detect food quality. This chapter also talks about real-time applications of the food quality detection system, delves into significant challenges, and articulates the research motivations that led to the proposal of the problem statement, which aims to create an AI-based food quality detection system. Milk adulteration poses serious health risks and affects the nutritional quality of milk. Ensuring the purity of milk being sold to consumers is paramount, and this thesis also proposes an AI-based detection system specifically for identifying adulterated milk.

The chapter culminates by dissecting the structure of the thesis, outlining proposed objectives, methodology adopted, and contributions to the field.

1.1 Food Quality: An Overview

Food quality encompasses the inherent characteristics and features of a food item that dictate its suitability, nutritional worth, and safety for consumption. These attributes contain sensory facets like flavour, consistency, scent, visual appeal, nutritional composition, packaging, and labelling. Many elements influence food quality, including ingredients, processing techniques, storage conditions, and handling procedures. For instance, produce harvested when perfectly ripe and stored under optimal circumstances are expected to exhibit superior quality compared to prematurely harvested items stored in unfavourable environments. The assurance of food quality is pivotal for safeguarding consumer well-being and upholding the reputation of food products. Diverse approaches, such as sensory assessment, chemical analysis, and microbiological testing, are available for monitoring and evaluating food quality. The establishment of food regulations and standards have a pivotal role in ensuring the quality and safety of the food.

1.1.1 Various Factors that affect Food Quality

Food quality is subject to a multitude of variables, giving rise to distinct categories of quality deterioration as outlined below:

- *Food Adulteration:* The reprehensible practice of food adulteration or fraud stems from economic motives and poses a significant threat to public health. This unethical pursuit of monetary gain involves introducing adulterants into food products to inflate profits, thereby endangering lives. Commonly affected items span dairy, grains, seafood, oils, alcoholic beverages, and honey. Fruits and vegetables found in markets are also not spared; they often harbor harmful chemicals and pesticides due to unscrupulous practices. Milk adulteration is another significant issue affecting public health, as milk sold often contains impurities and harmful substances. Common adulterants include water, detergents, urea, and synthetic milk, compromising its purity and nutritional value, posing serious health risks to consumers. Various methods are employed to compromise food quality, including removing valuable components, concealing poor-quality products with genuine ones, or even replacing authentic items with a substandard alternative. Food quality can also erode when unidentified substances are added or when toxic materials compose the packaging. Unsafe pesticides or other chemical substances sometimes find their way into the mix.

- *Food Contamination:* Natural processes can contaminate food, such as microorganisms deteriorating fruits, vegetables, milk and other dairy products, and perishable beverages, leading to spoilage.
- *Farming Practices:* Food cultivation, harvesting, and transportation greatly influence its quality. For instance, deploying pesticides, herbicides, and fertilizers can alter nutritional content and potentially introduce detrimental residues. Similarly, certain farming practices like monoculture can deplete soil nutrients, reducing crop quality .
- *Storage and Transportation:* The manner in which food is stored and transported directly impacts its quality. Improper storage can trigger spoilage or contamination, diminishing nutritional value and heightening the risk of foodborne illnesses. Transportation, especially for fresh produce, can induce wilting or damage that adversely affects quality.
- *Processing Methods:* Food processing techniques have an impact on quality, too. Processing may entail nutrient addition or removal and the introduction of preservatives or additives affecting safety and nutritional value. High-temperature cooking or irradiation, often employed in processing, can also lower nutritional content.
- *Food Additives:* Additives like flavourings, preservatives, and colourings can shape food quality. While certain additives are benign and might enhance nutritional value, others can pose risks if consumed excessively or over an extended period.
- *Environmental Factors:* The environment in which food grows can influence its quality. Environmental exposure, like heavy metals or pesticides, can undermine nutritional content and safety. Climate change affects temperature and rainfall patterns and impacts crop yields and nutritional composition.
- *Handling and Preparation:* How food is handled and prepared can significantly impact its quality. Poor hygiene during preparation can lead to contamination and foodborne illnesses. Overcooking or undercooking can also influence nutritional content.

Therefore, understanding these influences is fundamental for enhancing and maintaining high standards in food quality. The federal agencies involved in food safety are discussed in the following sub-section.

1.1.2 Federal Agencies with a Role in Food Safety

Federal agencies play a pivotal role in safeguarding food safety, serving as conduits for government-provided information. Federal agencies around the world play a vital role in ensuring food safety. These agencies regulate and monitor various aspects of the food supply chain, from production and processing to distribution and consumption.

Several agencies are dedicated to maintaining food safety standards on the global stage. For example, the *Food Safety and Inspection Service (FSIS)* guarantees the safety of meat, poultry, and egg products. Meanwhile, the U.S. *Food and Drug Administration (FDA)* shields consumers from impure, unsafe, or inaccurately labelled products. Similarly, the *Environmental Protection Agency (EPA)* is tasked with upholding drinking water supply safety. Additional worldwide agencies include the *Federal Trade Commission (FTC)* and the *Centers for Disease Control (CDC)*, among others [2].

In India, the *Food Safety and Standards Authority of India (FSSAI)* assumes the responsibility of regulating food safety standards, ensuring that the food available is safe for human consumption. Functioning independently under the aegis of the Ministry of Health and Family Welfare, the FSSAI is overseen by the Government of India. Its purview encompasses the realm of food safety and regulation within the country. The FSSAI controls the entire spectrum, including manufacturing, storage, distribution, sale, and imports, to ensure safety.

The subsequent section delves into the pressing need to develop a real-time food quality detection system.

1.2 Need for Food Quality Detection System

Ensuring our food's safety and nutritional value is critical, making food quality detection an indispensable process. The following reasons underscore the significance of food quality detection.

- *Safety:* The identification of harmful contaminants like bacteria, viruses, toxins, and other dangerous substances in food is facilitated by food quality detection. These contaminants have the potential to trigger foodborne illnesses, which can range from severe to fatal.
- *Nutritional Value:* Food quality detection is instrumental in gauging the nutritional content of edibles. This determination is pivotal, as our sustenance should deliver the essential nutrients and energy requisite for optimal health.
- *Compliance:* Ensuring conformity with regulatory standards and adherence to food safety regulations is a core facet of food quality detection. Shielding consumers from the perils of unsafe and substandard food products remains an imperative goal.

- *Consumer Confidence*: Establishing consumer trust in the products they purchase is a direct outcome of food quality detection. Companies renowned for producing secure, high-quality food items are more likely to garner consumer patronage.
- *Shelf Life*: The estimation of a food item's shelf life is facilitated by food quality detection. It is vital as it guarantees food preservation and safety over extended durations.

Hence, food quality detection is paramount in ensuring the safety, nutritional adequacy, regulatory compliance, and prolonged shelf life of our sustenance. The forthcoming section will delve into various methodologies employed for detecting food quality.

1.3 Food Quality Detection Methods

The food quality detection techniques vary from simple visual methods to complex systems. Ensuring the absence of contaminants in fruits, vegetables, milk and other dairy products through quality control tests constitutes a significant aspect of delivering uncontaminated consumables. Research has demonstrated that the techniques for food quality detection can be broadly divided into two parts. These categories encompass traditional methods for identifying food quality detection and automated techniques for detecting food quality. A comprehensive exploration of these techniques is presented in the subsequent subsections.

1.3.1 Traditional Methods to Detect Food Quality

Traditional approaches employed to identify food quality encompass uncomplicated chemical tests, olfactory assessment of food freshness, utilization of diverse electronic devices, and other hands-on, observation-driven methodologies. The subsequent section elaborates on various techniques employed in detecting food quality.

- *Electronic devices to identify food quality*: It is noted that a range of electronic devices are employed to discern food quality. Examples include the lactometer test, which gauges the milk's specific density, freezing point analysis for milk, and applying devices like lactoscan for digital milk analysis.
- *Laboratory tests using chemical substances*: Diverse laboratory examinations are carried out to assess substance quality. For instance, an array of pH indicators is employed, causing color alteration in the food when adulterants are detected. Distinct chemicals serve to ascertain contamination in food items. As an illustration, tincture iodine is utilized to identify starch presence in milk and its derivatives [3]. On the other hand, hydrochloric acid (HCl) is employed to pinpoint the presence of washing soda in

jaggery. The execution of these laboratory tests involves experts with extensive domain knowledge and a profound understanding of the chemical properties inherent to food products.

- *Manual inspection of food products*: This approach requires human involvement to assess food items for quality detection visually. Expert evaluators are essential to individually examine different adulterants and characterize their attributes. The manual inspection process relies on evaluating the visual characteristics, aroma, texture, and other relevant factors of the food products. Even these experienced professionals might encounter challenges in accurately predicting outcomes in some situations.
- *Observation-based methods to detect food quality*: Various observational methods are employed in domestic settings and on a small scale to identify adulterants in food products. For instance, a drop of milk is placed on a polished slanted surface to ascertain the presence of added water in milk. It is considered pure if the milk leaves a trace behind as it flows. Conversely, if the milk flows swiftly without leaving a trail, it is likely adulterated. Similarly, when examining coconut oil for other oils, placing it in a transparent glass and refrigerating it leads to solidifying coconut oil.

In contrast, other oils separate into distinct layers. Numerous additional techniques are employed to detect adulterants in diverse food products. For instance, heating and dissolving samples in water are commonly used approaches. Collectively, these methods aid in uncovering contaminants in various food items.

Conventional approaches to ensuring food safety are insufficient for effectively managing this concern. Hence, it is necessary to devise inventive and cutting-edge methods that could be utilized by the general public or individuals with limited expertise in this field. These techniques should be user-friendly and cost-effective tools to monitor food quality and achieve the desired objectives. To meet stringent quality criteria, researchers engage in extensive studies to guarantee that food items meet established standards. Their efforts involve pinpointing the specific types of bacteria present in the food while striving to fulfill consumers' expectations, particularly within food quality assurance; technology and scientific advancements are pivotal in driving progress within the food industry.

1.3.2 Automated Food Quality Detection Methods

Artificial Intelligence (AI) has assumed a predominant role in ensuring food safety and upholding quality standards. The food industry has adeptly harnessed the benefits of AI advancements. Within the food sector, there is a notable demand for enhanced product inspection, encompassing the assessment of food product quality and the classification and grading of fruits and vegetables. Similarly, in the dairy industry, ensuring the purity and quality of milk is crucial to safeguard consumer health and maintain trust in dairy products. The requisite data can be categorized into two forms to build an AI system capable of discerning food quality. The initial category of data is channelled into constructing a vision-based model. This model is primarily oriented towards appraising the quality of food items based on a spectrum of parameters, including color, texture, size, shape, defects, and morphological attributes. The classification process hinges on the physical characteristics of fruits, vegetables, and milk and other dairy products, with machine learning models employed to train the data [4].

The second data type revolves around parameters such as moisture content, pH levels, temperature, pressure, humidity, viscosity, and other pertinent attributes. These parameters serve the purpose of scrutinizing the chemical composition of food products. To facilitate this endeavour, the Internet of Things (IoT) comes into play by collecting data from various sensors. The identification of adulteration is contingent on the composition of the food products themselves. Contemporary equipment, including electronic tongues and electronic noses, harvests this data and subsequently conducts analyses to gauge food quality [5].

- **Vision-Based Methods**

The visual component holds immense importance in the evaluation of food quality. AI's role in enhancing food quality assurance is exemplified by employing computer vision systems that excel in identifying physical anomalies and impurities within food items. A technique known as the vision-based model harnesses images of food products to identify their quality. This is achieved by training the visual dataset using Machine Learning and Deep Learning models. These same models are equally adept at appraising food quality through the analysis of textual data.

- **IoT-Based Food Quality Detection Methods**

The combination of the Internet of Things (IoT) and AI has emerged as a robust framework for bolstering food security and safety. IoT technology can transform the adulteration detection system into an intelligent device. Moreover, it can improve food quality as an integral element of the food supply chain. It can be achieved through real-time tracking of food conditions and the seamless sharing of this data with consumers.

- **Quality Control of Food Using Modern Electronic Methods**

The utilization of AI in food quality is exemplified by its incorporation within machine learning algorithms to scrutinize extensive datasets containing sensory information like taste, aroma, and texture. This integration facilitates the detection of discernible patterns indicative of food quality. It ensures the uniformity of taste and texture across product batches. Among the innovative tools in this realm are the E-Nose and E-Tongue, which emulate human olfactory and gustatory capabilities through an assemblage of sensors. These systems find diverse applications within the framework of food adulteration detection [6]. When coupled with multivariate statistics, the intricate datasets derived from signals produced by E-Nose and E-Tongue form robust and swift tools for classifying, discriminating, recognizing, and identifying samples. Furthermore, these tools are proficient in predicting the concentrations of various compounds, amplifying their effectiveness.

1.4 Use of AI in Food Quality Detection

The food industry plays a pivotal role in both national and global economies. The urgency to uphold the quality and safety of food products has spurred the demand for intelligent solutions driven by AI. Adopting AI presents various opportunities within the food industry, encompassing precision farming, multiple aspects of food production and consumption, and quality control measures. This transformative shift is evident in how AI is reshaping perceptions of food production, quality assurance, delivery systems, and more, with the proliferation of intelligent mobile applications being a driving force.

Leveraging AI can effectively establish comprehensive food databases and conduct insightful analyses, fostering a healthier and more affordable food industry for workers and consumers. In contrast, current methods employed by enterprises to detect food adulteration are intricate, costly, and labor-intensive, necessitating specialized infrastructure and manual efforts. Addressing this, AI can facilitate the development of cost-effective automated systems, empowering end-users to evaluate the quality of fruits, vegetables, milk and other dairy products.

Hence, incorporating AI-based intelligent solutions within the food industry becomes essential to meet the evolving demands of society. These solutions can potentially boost farmers' crop yields while minimizing costs, thus augmenting their earnings. Contemporary techniques like electronic tongues, electronic noses [7], computer vision [8], and spectral imaging [9] are increasingly harnessed for food quality detection. These methods generate substantial digital data regarding food composition and attributes, demanding sophisticated analysis for extracting valuable insights. AI-based methodologies, such as partial least squares [10], artificial neural networks (ANN), support vector machines (SVM) [11], random forest [12], and k-nearest neighbour (KNN) [13], among others, offer viable means to assess data and glean meaningful information. Techniques like principal component analysis (PCA) [14], wavelet transform (WT) [15], independent component correlation algorithm (ICA) [16], scale-invariant feature transform [17], histogram of oriented gradient [18], and more serve as indispensable tools for data analysis and feature extraction [5].

The prevailing awareness regarding the decline in food quality has spurred researchers to delve into this domain, prompting exploration and investigation. The ensuing section discusses various applications of food quality detection systems.

1.5 Applications of Food Quality Detection System

Food quality detection systems find wide-ranging applications throughout the food industry, encompassing the following areas:

- *Quality control in food production:* These systems guarantee that food items adhere to stipulated quality standards. This safeguards against the circulation of flawed products in the consumer market, curbing the potential for foodborne illnesses and safeguarding a company's reputation.
- *Food safety monitoring:* Food quality detection systems serve as tools for overseeing the safety of food commodities by identifying the existence of harmful impurities, such as bacteria, viruses, or toxins
- *Shelf-life prediction:* These systems can anticipate the duration of a food product's shelf life by continuously evaluating its quality over time. This proactive measure guarantees that items are ingested before they succumb to spoilage or become unsuitable for consumption.
- *Freshness detection:* By assessing variables like pH, temperature, and gas concentrations, food quality detection systems ascertain the freshness of edibles. This contributes to consuming products at their zenith of freshness, enhancing taste and nutritional content.

- *Sorting and grading:* The utilization of food quality detection systems in sorting and categorizing edibles based on attributes such as dimensions, color, and consistency assures the precise classification of products. This helps to ensure that products are sorted and graded accurately, improving the efficiency of the food production process.
- *Quality assurance in distribution:* These systems play a pivotal role in substantiating that food items are transported and stored under optimal conditions, consequently preserving their quality and safety during distribution.
- *Consumer feedback:* Food quality detection systems can collect consumer feedback on food products, enabling companies to improve the quality of their products based on consumer preferences and expectations.

1.6 Open Challenges in Food Quality Detection System

Developing a food quality detection system is an intricate endeavour with various challenges. Among the critical hurdles encountered are as follows.

- *Diverse Food Properties:* Food items exhibit extensive diversity in their attributes—ranging from shape, color, texture, and size to moisture content. These disparities can complicate developing a detection system capable of consistently ascertaining the quality of disparate food products.
- *Complex Interactions:* Food quality is not just a single factor but a complex combination of factors such as nutritional content, taste, texture, appearance, and freshness. It is challenging to develop a system that can accurately measure all these factors and their interactions.
- *Limited Training Data:* Developing a machine learning-based detection system requires much training data. However, obtaining and labeling high-quality food data can be complex and may be subject to variations and bias.
- *High Accuracy Requirement:* In food quality detection, accuracy is paramount. Any error in detecting food quality can have serious consequences, such as foodborne illnesses, waste, and economic losses. Therefore, developing a detection system that can reliably and accurately detect food quality is a challenge.
- *Environmental Interference:* The detection system needs to function in various environments, including varying temperatures, humidity levels, lighting conditions, and noise levels. These environmental factors can affect the accuracy of the system and need to be carefully considered during the development process.

- *Cost-Effectiveness:* Developing a food quality detection system can be costly, and the system needs to be cost-effective to be adopted by the food industry. Balancing cost and effectiveness can be challenging.
- *Regulatory Compliance:* Food quality detection systems must comply with various regulations and standards, such as food safety and quality regulations, privacy regulations, and data protection laws. Meeting these requirements can be challenging and may require collaboration with regulatory bodies.

Therefore, developing a food quality detection system requires a multidisciplinary approach that considers various factors, such as food properties, machine learning, data labeling, environmental factors, and regulatory compliance.

1.7 Motivation for the Development of Food Quality Detection System

Consuming unhealthy food elevates the susceptibility to illnesses, obesity, and scarcity of essential nutrients. The contemporary generation is progressively attuned to the significance of adopting a wholesome lifestyle and places considerable emphasis on the caliber of their sustenance. Creating an AI-driven, automated food quality detection system holds the potential for various advantageous outcomes. Such a system can play a pivotal role in guaranteeing the safety and excellence of our food. By harnessing sophisticated AI algorithms and techniques from machine learning, this system can discern contaminants, additives, and other pollutants in food items.

Furthermore, an automated system for detecting food quality can refine the efficiency and expeditiousness of both food processing and inspection. It can potentially truncate the time and resources that would otherwise be expended on manual evaluations and tests of food commodities. Consequently, this can culminate in economic benefits for manufacturers and processors within the food industry. Thirdly, an AI-grounded system can furnish more precise and uniform results than those achieved through human inspection. This facet can substantially mitigate the probability of inaccuracies and contradictions within the assessment of food quality, mitigating the profound repercussions of such discrepancies on communal health.

Hence, developing an AI-based automated food quality detection system can significantly improve food safety and quality while increasing efficiency and reducing costs for the food industry.

1.8 Research Gaps

Considerable research efforts have been directed toward establishing robust protocols for upholding food quality standards. However, the Indian market continues to grapple with substantial obstacles arising from the underdeveloped state of technological advancements in food quality detection. The emergence of AI-driven automated food quality detection represents a swiftly burgeoning domain of study. Nevertheless, constructing an AI and sensor-based framework for discerning food quality is accompanied by distinctive challenges listed below.

- *Lack of Standardization*: There is a need for data collection and labeling standardization to ensure that the models are trained on high-quality data.
- *Limited Data Availability*: The scarcity of extensive, well-annotated datasets for diverse food categories remains a formidable hurdle in developing AI-powered food quality detection systems.
- *Need for Robustness*: AI models must be able to handle variations in different types of foods and their quality attributes. Models must be robust enough to handle variations in lighting, camera angles, and other factors that can impact image quality.
- *Real-time Detection*: Developing real-time food quality detection systems enables rapid quality inspection and decision-making in the food processing and packaging industries.
- *User Acceptance*: User acceptance of AI-based food quality detection systems is crucial, and ensuring that the technology is user-friendly and easy to use is essential.
- *Integration with Existing Systems*: The seamless integration of AI-based food quality detection systems with pre-existing quality control mechanisms is indispensable for guaranteeing the effective deployment of this technology within industrial frameworks.
- *Interoperability and Data Sharing*: Developing interoperable data-sharing platforms for food quality detection is critical to enable collaboration between researchers and industry partners and accelerate the development and deployment of AI-based systems.

1.9 Objectives

The main objective of the proposed research work is to develop a food quality detection system. The following objectives are proposed based on the research gaps.

1. To study and analyze existing techniques for food quality detection.
2. To perform the data collection using relevant datasets from different sources.

3. To perform preprocessing and identify essential features for developing the ML-based food quality detection system for commonly used fruits and dairy products.
4. To propose and implement the system to detect food quality.
5. To test and validate the proposed system.

1.10 Research Methodology

A meticulous research methodology has been diligently pursued to attain the research objectives.

To achieve the first objective:

- An extensive literature survey has been undertaken. This survey comprehensively explores diverse research methodologies for food quality detection. It also serves as a means to gain insights into the existing landscape of food quality detection systems.
- A comprehensive review of relevant studies has been conducted. This encompasses an exhaustive analysis of esteemed electronic conferences at the national and international levels and reputable journals and databases germane to the research domain.
- An advanced search mechanism rooted in keyword usage has been meticulously executed. This method has facilitated the curation of pertinent research articles from electronic repositories.
- A carefully crafted set of research inquiries has been formulated. This set of questions has been systematically employed to explore the gamut of research studies. The research undertaking has entailed a meticulous survey of diverse categories of food products. This exhaustive exploration is undertaken to craft a food quality detection system that is comprehensive and robust.

To achieve the second objective:

- A thorough analysis of online datasets pertinent to varying food categories has been carried out to serve the research objectives within this domain.
- A fruit dataset has been carefully created. This compilation has been realized through visits to assorted fruit markets, street-side fruit vendors, and retail outlets. The images have been captured from many angles and against diverse backdrops. This diverse collection has been realized using high- and low-resolution cameras, ensuring comprehensive coverage.
- Some fruit images have also been sourced from existing public datasets [19], [20], [21], [22] to expand the dataset, enhancing the variety and comprehensiveness of the

collection. These publicly available resources enriched the dataset for analysis and research purposes.

- A real-time milk dataset has been meticulously assembled. This effort entailed the collection of assorted milk samples, thereby facilitating the acquisition of their corresponding constituents. This dataset proves instrumental in the formulation of a machine learning-based system for the detection of milk quality.

To achieve the third objective:

- The dataset has undergone comprehensive preparation procedures. It entailed augmenting the images through mosaic data augmentation, applying diverse noise removal and image sharpening filters, and additional processing steps. These processes collectively contribute to formulating a system that identifies fruits and detects their quality.
- Diverse manual and automated techniques for feature extraction and data preprocessing have been diligently employed to fabricate a system capable of predicting tomato ripeness and shelf life. Data enhancement includes meticulous cleaning to eliminate noise and outliers, augmenting data quality. The array of features chosen for model training encompasses handcrafted and automated features derived from a Convolution Neural Network (CNN) deep learning model. The curation of pertinent features is achieved through the application of the Principal Component Analysis (PCA) feature reduction technique.
- As for the milk dataset, an essential preprocessing phase has been enacted to ensure its conformance to the requisite format. This preprocessing is a pivotal step in laying the groundwork for a milk classification system that hinges on detecting adulterants.

To achieve the fourth objective:

- Many ML and DL methodologies have been employed to train the system. These approaches have been coupled with various feature extraction techniques, constituting the foundation for creating fruit and milk quality detection systems.
- A cutting-edge, real-time AI-driven fruit identification and quality detection system rooted in the CNN object detection framework has been conceptualized. This model functions in a dual-phase manner. During the initial phase, fruit identification is executed, followed by the subsequent phase, where fruit quality detection is undertaken.
- An innovative ensemble approach has been put forth to predict the ripeness and shelf life of tomatoes, employing machine learning regression techniques.

- A novel AI-driven IoT-based sensor system has been proposed to tackle milk adulteration detection. This system employs artificial intelligence to classify milk samples based on the presence of a range of adulterants.

To achieve the fifth objective:

- An evaluative comparison is carried out to measure how effectively the proposed systems perform compared to a range of existing state-of-the-art methodologies. This evaluation hinges on diverse standard performance metrics.
- Traditional performance metrics have been scrutinized, encompassing pertinent accuracy parameters for all three proposed systems. These contain accuracy, precision, recall, specificity, F measure, and correlation (R2), among others.
- Various graph analyses about training and testing accuracy and loss for the object detection model have been undertaken. These evaluations have been compared with similar assessments of other cutting-edge models within the field.

1.11 Research Contribution

The principal contribution of this thesis resides in developing an AI-driven food quality detection system. The comprehensive impact of this thesis unfolds as below.

- An extensive literature review on various approaches to identify food quality, different products, factors considered while evaluating food quality, ML and DL applications in food have been explored. The existing systems, key challenges, and comparison with the state-of-the-art models are presented in our thesis work.
- The research extends to a thorough analysis of online datasets covering various food categories, forming a foundational basis for research within this domain.
- A fruit dataset has been curated through direct visits to different locales, such as fruit markets, roadside stalls, and shops. These images have been captured from varying angles and diverse backgrounds, utilizing high and low-resolution cameras.
- A parallel effort has been invested in collecting a milk dataset. This dataset has been constructed by collecting various milk samples, each designed to capture their corresponding compositional attributes. This dataset underlies the development of a machine learning-based milk quality detection system.
- A novel, real-time AI-driven approach has been proposed for fruit identification and quality detection. This approach leverages the CNN object detection framework and

operates in two distinct phases: identifying fruits in the initial phase and detecting fruit quality in the subsequent step.

- A pioneering ensemble approach has been formulated to predict the ripeness and shelf life of tomatoes, utilizing machine learning regression techniques.
- An innovative IoT sensor system empowered by AI is introduced to detect milk adulteration. This sophisticated system performs classification on milk samples to detect the presence of various adulterants.

1.12 Thesis Organization

The thesis is organized into seven chapters, and a brief overview of these chapters is provided below.

Chapter 1 elucidates the necessity for a system to detect food quality by outlining various elements that influence it. The chapter further acquaints us with methods for identifying food quality, including manual and automated approaches. This chapter includes the real motivation behind the research. Also, it covers the diverse applications of food quality detection system. The chapter concludes with the challenges and research gaps, sets forth research objectives, delineates the methodology employed, enumerates the valuable contributions of the thesis, and provides the thesis organization. The subsequent chapters of the thesis are intricately linked with these outlined objectives.

Chapter 2 furnishes a comprehensive exploration of the existing research landscape concerning food quality. This chapter meticulously examines, condenses, and assesses the present state of knowledge in food quality. The methodology adopted for conducting the literature review is rigorously defined. The review provided within this chapter stems from the meticulous identification of pertinent research materials from reputable electronic databases and prominent conferences associated with this field. A judicious application of inclusion and exclusion criteria has been exercised to refine the selection of studies. Subsequently, the collected findings are organized chronologically based on their year of publication. Various sources encompassing workshops, conferences, and journals have been tapped into to procure the research articles. Additionally, this chapter expounds upon freely accessible online datasets relevant to the subject matter.

The chapter examines distinct food quality detection techniques employing the IoT, machine learning, and deep learning. It also expounds upon the array of research initiatives scholars undertake across various categories of food products. A graph is included to provide a visual representation of the ascending interest in food quality detection research over the years, aiding researchers in staying abreast of the latest trends and developments in the field.

Chapter 3 talks about the comprehensive architecture of the proposed AI-based food quality detection system. It provides an overall picture of the whole work presented in the thesis. The data used to construct AI models to enhance food quality detection systems can manifest in diverse forms and applications. The proposed methodology primarily revolves around the assessment of fruits and milk products. The entire work has been divided into three main components: a system for fruit identification and quality detection using object detection and a machine learning-based approach for assessing tomato ripeness and estimating shelf life. Furthermore, an intricately designed real-time AI-integrated, cost-effective IoT-based multi-sensor system has been developed to address milk adulteration. The detailed working of these segments has been discussed in the subsequent chapters.

Chapter 4 delves into the significant realm of automated fruit identification and quality assessment, a vital pursuit within the fruit industry. The pivotal role of fruit sorting in ensuring quality, particularly for export endeavors and comprehensive evaluation, accentuates the necessity for such systems. A two-tier system is conceptualized as a strategic response to address the twin objectives of precise fruit identification and comprehensive quality appraisal. The study strategically harnesses the capabilities of the YOLOv5 object detection system to engineer a specialized model. This intricate process encompasses a meticulous dataset preparation stage, wherein innovative mosaic data augmentation techniques are employed for image refinement, bolstered by a diverse array of noise removal filters and supplementary processing stages. Within this dataset, a compilation of images showcases four distinct categories of fruits: apples, bananas, oranges, and tomatoes. These images have been captured from various angles and against varying backgrounds, employing cameras with high and low resolutions. These images have been sourced from fruit markets, shops, roadside fruit stands, and comparable settings. This extensive dataset equips the AI system to grasp nuances encompassing zoom, contrast, and color saturation. The yardstick of the proposed system's effectiveness is its predictive performance. After rigorous training on the distinctive features gleaned from the dataset, the model's capacity to accurately predict labels for testing samples underscores its operational prowess and efficiency in real-world applications.

Chapter 5 describes the substantial contribution of manual and automated techniques to extract pertinent features from tomato fruits. These features are harnessed to assess the fruits' quality based on parameters like ripeness and suitability. The chapter introduces an ensemble machine learning strategy, employing regression methods to predict critical factors: the tomato's ripeness and usefulness, significantly influencing its shelf life. The formulation of the proposed model necessitates the acquisition of an image dataset thoughtfully gathered through field visits encompassing diverse market vendors. This dataset then undergoes meticulous data cleansing procedures, effectively removing noise and outliers to enhance its integrity. The training of the model hinges on a selection of features, encompassing both handcrafted attributes and automated features generated via a CNN deep learning model. The efficacy of the proposed system is rigorously validated through a comparative analysis against existing models utilized to evaluate tomato quality. Gratifyingly, the outcomes derived from this validation process serve to affirm the notable effectiveness of the proposed methodology.

Chapter 6 discusses an innovative AI-driven IoT-based multi-sensor system explicitly designed for milk adulteration detection. Milk is a vital nutritional resource, and ensuring its quality and safety is paramount. Traditional methods for spotting adulteration have demonstrated shortcomings, prompting the pursuit of a more sophisticated and automated solution. The system's ingenuity lies in integrating diverse sensors capable of real-time measurements, spanning pH, electrical conductivity (EC), temperature, gas parameters, and Volatile Organic Compounds (VOC) parameters. This comprehensive approach quantifies key constituents within milk samples, including Fat, Protein, Solids, Not Fat (SNF), Lactose, and Gravity values. To discern specific adulterants like Urea, Starch, Sodium Bicarbonate, Maltodextrin, and Formaldehyde, a machine learning-based ensemble technique is adroitly employed for adequate classification. Central to this study's significance is the conception of an IoT-based data acquisition device harmoniously synced with the sensor system. This synergy facilitates accurate and efficient measurements. Moreover, the integration of SHAP (SHapley Additive exPlanations) analysis contributes depth by illuminating the ensemble model's decision-making process, thereby enhancing the overall interpretability of the findings.

Chapter 7 concludes the research work presented in this thesis and presents the future implications. The proposed AI-driven food quality detection system holds significant potential to revolutionize the food industry. It aims to bring about transformative changes by ensuring safety, transparency, and sustainability throughout the food production and distribution processes. These advancements are poised to benefit both producers and consumers, ultimately contributing to a more reliable and healthier food supply. However, there is room for further extension and improvement of the current system to enhance its utility and applicability across the industry. The future of food quality detection, particularly in milk and fruits, envisions a convergence of state-of-the-art technologies focusing on precision, transparency, and empowering consumers. Ongoing research, technological innovation, and collaborative efforts within the industry will play a crucial role in shaping the landscape of food quality detection. This concerted effort will ensure the consistent delivery of safe and high-quality food products to consumers worldwide.

Chapter Summary

The chapter thoroughly explains the importance of having a reliable food quality detection system by detailing various factors that impact it. It introduces us to multiple methods for gauging food quality, encompassing manual and automated techniques. The primary motivation driving the research is highlighted in this chapter, underscoring the critical need for enhancing food quality assessment. Additionally, the chapter explores the wide-ranging applications of food quality detection systems. Towards the end, it addresses the existing challenges and research gaps, outlines research objectives, describes the methodology employed, emphasizes the valuable contributions made by the thesis, and offers an overview of the organization and structure of the thesis.

Chapter 2

Literature Review

The increasing worry regarding consuming high-quality food has amplified the need for scrutiny, identification, and intervention. In recent periods, instances of the deterioration of food quality through various unjust means have been rapidly surging. This literature provides a comprehensive examination of research on food quality from the last decade.

This chapter critically assesses, summarizes, and evaluates the current landscape of food quality content. The comprehensive workflow of the entire chapter is visualized in Figure 2.1. Section 2.1 elaborates on the methodology employed for the literature review. It outlines the structured approach, framing research questions and using a systematic review technique to analyze pertinent research articles meticulously. These articles, focusing on various methods for food quality detection, are organized based on their timelines and sources, covering both conference and journal publications.

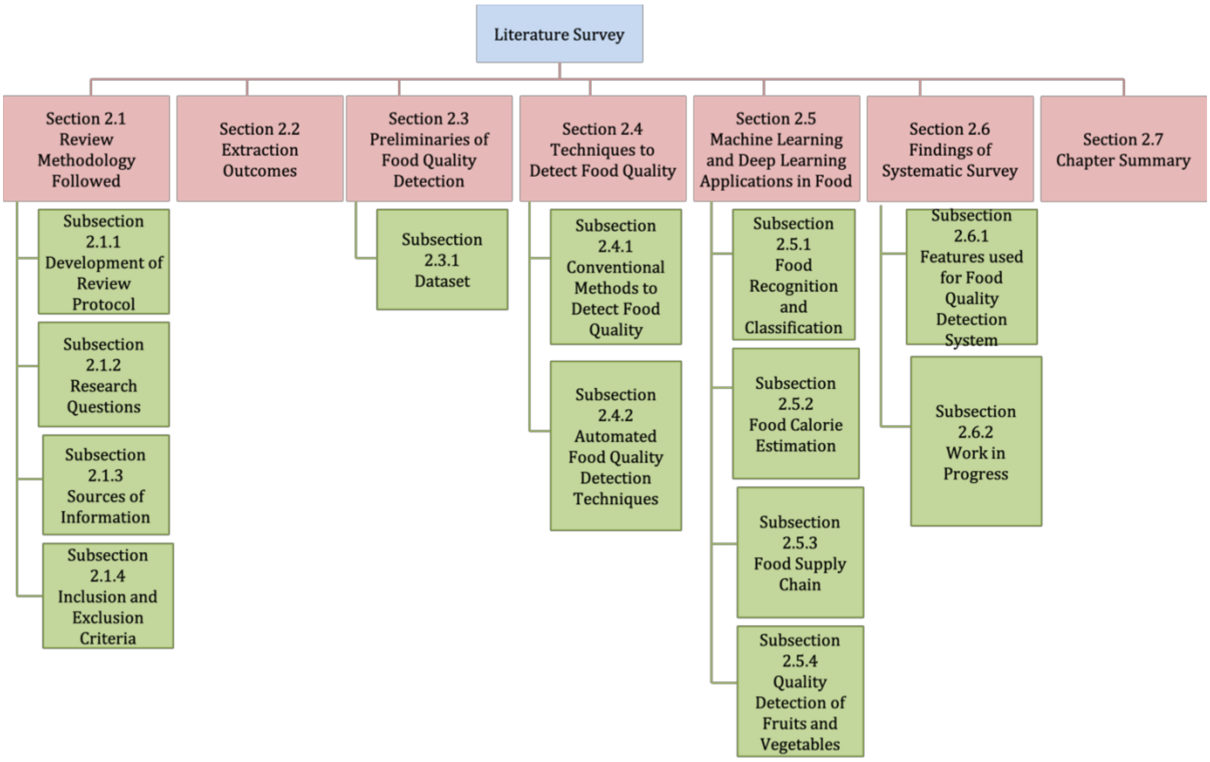


Figure 2.1. Organization of the Chapter Literature Review

Section 2.2 describes the extraction outcomes of the review. An exploration of available online datasets covering a range of food categories, which serve as valuable resources for research in this field, is discussed in Section 2.3. The methods for identifying food quality are thoroughly investigated and presented in Section 2.4. Additionally, this survey comprehensively explores applications of both ML and DL within the food quality domain in Section 2.5. This section delves into food recognition and classification, food calorie estimation, and quality detection of fruits and vegetables. Section 2.6 provides insights into the systematic survey's findings, discussing features utilized in food quality detection systems and existing assessment systems for food quality. Moreover, it presents research endeavours by scholars related to various food products. Finally, Section 2.7 concludes the chapter with a summary of its content.

2.1 Review Methodology followed

The review of food quality detection using machine learning and deep learning methods has been conducted using the following steps.

2.1.1 Development of Review Protocol

A systematic review methodology is employed to undertake the review process. Esteemed electronic databases and prominent conferences relevant to the field of research have been referenced for conducting the review. Subsequently, the number of chosen studies has been refined by adhering to inclusion and exclusion criteria. Following this, research inquiries are formulated to finalize the selection of research studies, and the outcomes are aggregated through meticulous analysis.

2.1.2 Research Questions

A comprehensive literature review outlined in the chapter is built upon an extensive survey of existing literature aimed at understanding the diverse methodologies employed by researchers for identifying food quality. To facilitate the efficacy of the systematic review, a set of questions has been designed, as documented in Table 2.1.

2.1.3 Sources of Information

Before initiating the search process, a suitable set of electronic databases has been considered to ensure the exclusive identification of pertinent research papers. The chosen databases include Google Scholar (www.scholar.google.co.in), Science Direct (www.sciencedirect.com), IEEE Xplore (www.ieeexplore.ieee.org), and Taylor & Francis (https://www.tandfonline.com/). These selections have been made to examine the corpus of research studies thoroughly. Most food safety and machine learning papers have been presented at esteemed conferences, encompassing virtually all papers within Google Scholar's database. As part of the final curation of research articles, redundant entries from Science Direct and IEEE Xplore have been subsequently removed.

Table 2.1. Research questions for systematic literature review

Research Questions	Motivation
RQ1: How are publications distributed across different years, and what are the primary sources of research articles related to detecting food quality?	Determine the period and origins of publications during which significant research studies have been carried out.
RQ2: Which annotated datasets are available online for food quality detection?	Identify accessible annotated datasets, presented in both image and textual formats, intended for conducting food quality detection.
RQ3: What are different techniques followed to detect food quality?	To figure out the methods based upon sensors and images, spectroscopy, etc., that can detect adulteration in different food products.
RQ4: What are the various applications of deep learning and machine learning in food?	Find out the various utilities of machine learning and deep learning in the food domain.
RQ5: Which food items have predominantly been investigated so far for quality detection?	Investigate the food items that have been the subject of most research efforts.
RQ6: What are various factors considered for food quality evaluation?	Identify the factors such as freshness, taste, *etc*., for which food analysis is performed.
RQ7. Which are the existing systems designed for assessing food quality?	Follow the literature thoroughly to discover the similar experiments the researchers did to evaluate the food quality.
RQ8: What are future research potentials from the review?	Identify various research domains that remain unexplored in this context.

2.1.4 Inclusion and Exclusion Criteria

An organized search based on keywords is conducted to extract pertinent research studies from electronic databases, as outlined in Table 2.2.

This study encompasses quantitative and qualitative research papers from the past decade, ensuring a comprehensive analysis of food quality detection. The keywords "food quality" and "food safety" yielded substantial outcomes when employed to search for research articles, reflecting the diverse perspectives within this field. The abstracts and titles of papers have been examined using the search phrase "Food quality detection [with, using, by] [Technique_used]."

Table 2.2. Keyword-based advanced search from the year (2009–2023)

Source	Keywords	Publication	Number of Results
Google Scholar	Food quality [with, using, by] [Technique_used]	C/J/M	150
	Food Safety [with, using, by] [Technique_used]		
	The freshness of fruits and vegetables [with, using, by] [Technique_used]		
Science Direct	Abstract, Title, Keywords: Food quality [with, using, by] [Technique_used]	J	75
	Abstract: Food Safety [with, using, by] [Technique_used]		
IEEE Xplore	Abstract: Food quality [with, using, by] [Technique_used]	C	55
	Abstract: Food Safety [with, using, by] [Technique_used]		
Taylor &Francis	Abstract, Title, Keywords: Food quality [with, using, by] [Technique_used]	J	45
	Abstract, Title, Keywords: Food Safety [with, using, by] [Technique_used]		

Technique_used: [IoT, Machine Learning, E-Nose, E-Tongue], C: Conferences, J: Journals

The different research studies use multiple ways of writing the same title. Hence, all these options have been considered while searching the related studies, so all research articles should be considered. Research from diverse journals and conferences, as well as Ph.D. and Master's Thesis, have been reviewed, employing an exclusion principle at different stages, as illustrated in Figure 2.2.

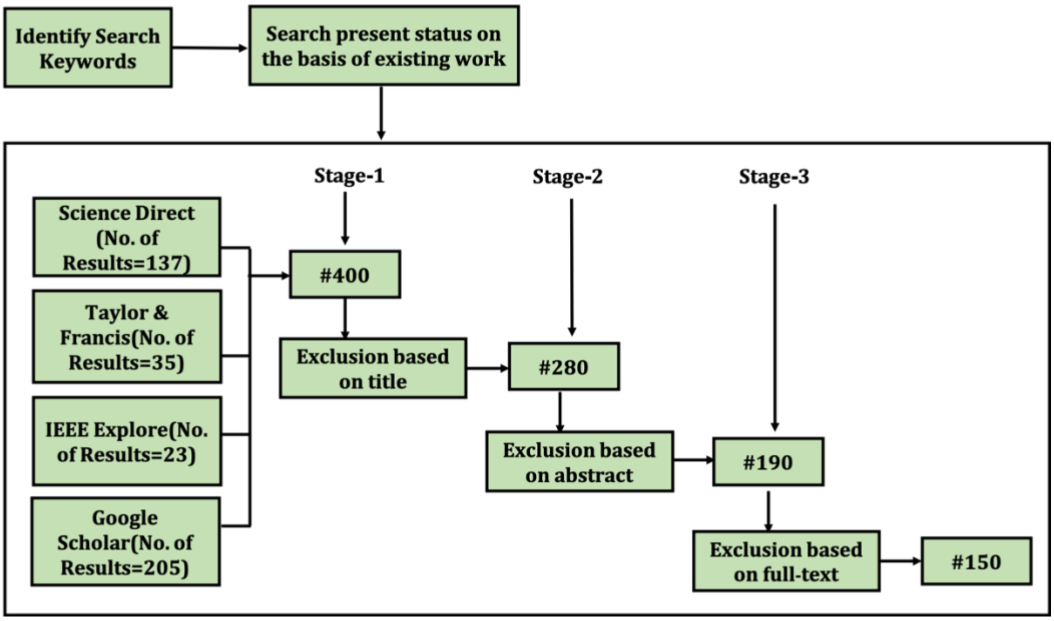


Figure 2.2. Review Technique followed

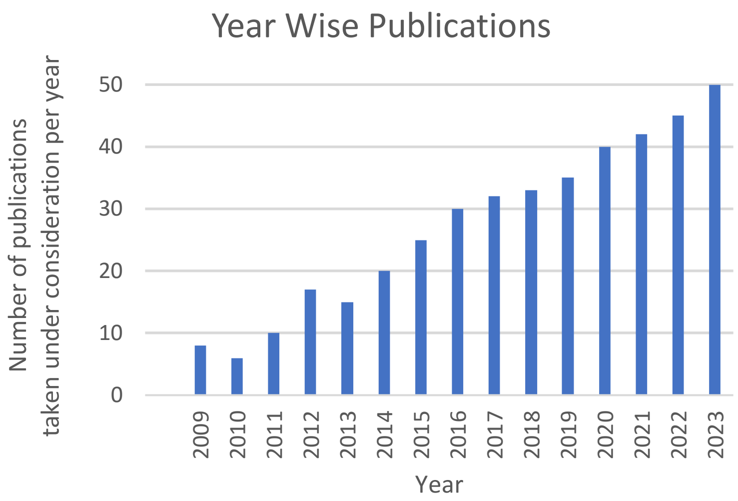
Our initial search yielded 400 research studies, as shown in Figure 2.2. These studies were filtered based on their title, resulting in 280 articles. Further refinement based on their abstracts narrowed the selection down to 190. Subsequently, the articles were reduced to 150 based on full-text review. These 150 research articles underwent a comprehensive examination to determine the final list of selected research articles ultimately.

2.2 Extraction outcomes

The main aim of this review is to explore current research regarding the utilization of AI in detecting food quality. This objective is formulated as research questions detailed in Table 2.1. In addressing research question RQ1, i.e., "How are publications distributed across different years, and what are the primary sources of research articles related to the detection of food quality?", the annual progression of research endeavours concerning the utilization of AI for food quality detection methods is illustrated in Figure 2.3 (a). The sources of publication origins are visualized in Figure 2.3 (b).

Presently, the domain of food quality assessment stands as a vibrant and formidable research arena. Consequently, the year-wise distribution of publications from the past decade is showcased in Figure 2.3 (a) to highlight the steady growth observed in research within this sphere over recent years. Through comprehensive analysis, it becomes evident that a substantial portion of research articles addressing food quality detection are disseminated through diverse conference proceedings and reputable journals.

The breakdown reveals that conferences encompass approximately 22% of these research articles, while journals encompass 72%. The remaining 6% are distributed among theses and online reports, as illustrated in Figure 2.3 (b). Journals command the highest share of research publications, followed by conferences.



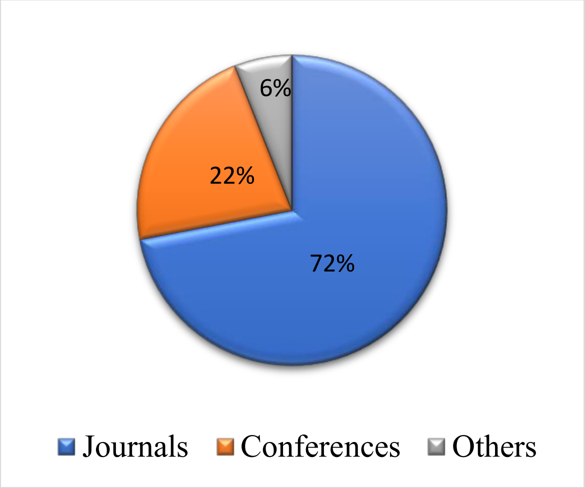


Figure 2.3 (a). Year-wise publications on food quality detection methods

Figure 2.3 (b). Status of publications of food quality detection articles from different sources

2.3 Preliminaries for Food Quality Detection

2.3.1 Dataset

The initial stage in conducting food adulteration detection involves the collection of datasets. Typically, researchers have devised their tailored datasets in alignment with their specific requirements and the pertinent parameters crucial for evaluating food quality. Some annotated datasets encompassing images of fruits, vegetable compilations, and a handful of datasets featuring cuisine from various countries are accessible online, as enumerated in Table 2.3. These datasets encompass a variety of images depicting diverse fruits, vegetables, and dishes. Since a substantial portion of research has concentrated on food recognition and categorization, these datasets are predominantly designed to cater to such objectives.

The details presented in Table 2.3 play a pivotal role in addressing research question RQ2, i.e., “Which annotated datasets are available online for food quality detection?”. This tabular representation offers a brief overview of the annotated datasets readily accessible online, encompassing various food items.

Table 2.3. Summary of annotated datasets for food quality detection

Dataset	Dataset Details	Model and Reference	Link
Food-101	101 food categories that include 1000 images per category	CNN-FOOD (Yanai et al. 2015) [23] Multitask (Wu et al. 2016) [24] Inception V3 Network (Hassannejad et al., 2016) [25] DeepFood (Liu et al., 2016a) [26] FoodNet (Pandey et al. 2017) [27] ResNet (Fu et al., 2017) [28] Inception Module (C. Liu et al., 2018) [29] Author-defined Model (Heravi et al. 2018) [30] ResNet-50 (Ciocca et al. 2018) [31] Inception V3 Model (Zheng et al. 2018) [32] wide-slice residual networks (WISeR) (Martinel et al.2018) [26], [33]	https://www.kaggle.com/dansbecker/food-101/home
UECFood-256	256 categories of Japanese food	DeepFoodCam (Kawano & Yanai, 2014) [34] CNN-FOOD (Yanai & Kawano, 2015) [23] Inception V3 (Hassannejad et al., 2016) [25] DeepFood Network (Liu et al., 2016a) [26] ResNet (Fu et al., 2017) [28] ResNet-50 (Ciocca et al., 2018) [31] Inception-v3+FP-CNN (Zheng et al., 2018) [32] The author defined (Heravi et al., 2018) [30] Inception Module (C. Liu et al., 2018) [29] WISeR (Martinel et al., 2018) [33]	http://foodcam.mobi/dataset256.html

Dataset	**Dataset Details**	**Model and Reference**	**Link**
UEC Food-100	Images of 100 kinds of Japanese food with at least 100 images per category	DeepFoodCam (Kawano & Yanai, 2014) [34] CNN-FOOD (Yanai & Kawano, 2015) [23] DeepFood (Liu et al., 2016a) [26] Inception V3 (Hassannejad et al., 2016) [25] MultiTaskCNN (Chen & Ngo, 2016) [35] ResNet (Fu et al., 2017) [28] Inception-v3+FP-CNN (Zheng et al., 2018) [32] Inception Module (C. Liu et al., 2018) [29] WISeR (Martinel et al., 2018) [33]	http://foodcam.mobi/dataset100.html
Fruit-360	90483 images of 131 categories of fruits and vegetables	CNN EfficientNet (Chung and Tai, 2019) [36] CNN (Sakib et al., 2019) [37] CNN (Bobde et al., 2021)[38]	https://www.kaggle.com/moltean/fruits
FIDS30	971 diverse images of 30 fruit categories, with around 32 images in every class	CNN (Hussain et al., 2018) [39] CNN LeNet (Sun et al. 2019) [40] Mimma et al.(2022)[41]	https://www.vicos.si/Downloads/FIDS30
Food 5K	The dataset contains 2500 food and 2500 non-food images	W. Jia et al. (2018) [10] McAllister, Zheng, Bond, and Moorhead (2018) [42]	grebvm2.epfl.ch/lin/food/Food-5K.zip

Dataset	Dataset Details	Model and Reference	Link
Food-11	16643 images grouped into 11 food categories (Bread, Dairy products, Dessert, Egg, Fried food, Meat, Noodles, Pasta, Rice, Seafood, Soup, Vegetable, and Fruit.	Abdulkadir SENGÜR et al. (2019) [43]	grebvm2.epfl.ch/lin/food/Food-11.zip
Lemon dataset	Lemon Quality Control Dataset	Bird et al.(2021) [44]	https://github.com/softwar emill/lemon-dataset
FruitNet	19000 images in three different categories: Bad Quality, Good Quality, and Mixed Quality for 6 different fruits (Apple, Banana, Guava, Lime, Orange, and Pomegranate)	Morshed et al.(2022) [45] Meshram et al.(2022) [46]	https://www.kaggle.com/datasets/ryandpark/fruit-quality-classification
Fruit Classification dataset	761 images of apples, coconuts, grapes, limes, oranges, tomatoes, bananas, and guavas.	Mimma et al.(2022) [41]	https://github.com/SumonAhmed334/dataset_fruit

2.4 Techniques to Detect Food Quality

Food quality detection methods range from uncomplicated visual techniques to intricate systems. Ensuring adulterant-free products for consumption involves significant quality control tests for fruits, vegetables, and dairy items.

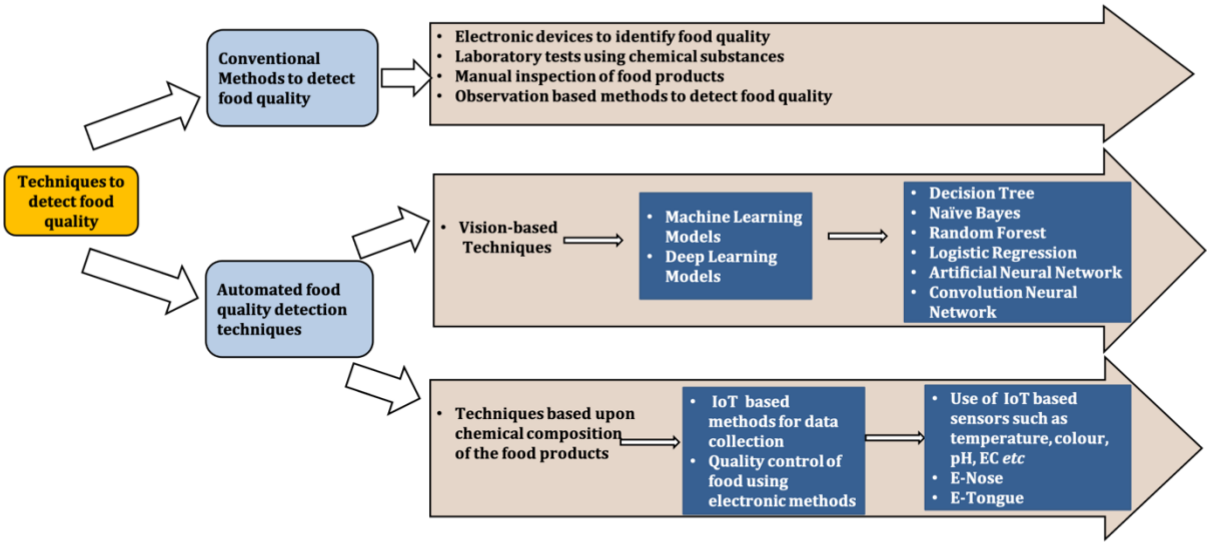


Figure 2.4. Methods to detect food quality

To respond to research question RQ3, i.e., "What are different techniques followed to detect food quality?" an examination reveals that techniques for detecting food quality can be broadly categorized into two groups, as illustrated in Figure 2.4. These categories encompass Conventional methods for detecting food quality and Automated food quality detection techniques. The subsequent subsections delve into a comprehensive discussion of these techniques.

2.4.1 Conventional Methods to Detect Food Quality

The conventional approaches employed for food quality detection encompass basic chemical tests, sensory assessments based on odour to determine food freshness, diverse electronic devices, and other manual techniques relying on observation. Below are several of the methods utilized to identify food quality

- ***Electronic devices to identify food quality:*** Various electronic instruments have been noted for their utility in detecting food quality. Examples include the lactometer test, which gauges milk's specific density, the determination of milk's freezing point, and using the lactoscan device for digital milk analysis.

- ***Laboratory tests using chemical substances:*** Diverse laboratory examinations are conducted to check the presence of contaminants. For instance, pH indicators are used to change food color when an adulterant is present. Various chemical agents are employed to identify quality; for instance, tincture iodine is used to detect starch in milk products [3], and hydrochloric acid (HCl) is employed to discern washing soda in jaggery. Such laboratory tests necessitate expert involvement of individuals well-versed in the chemical properties of food items.
- ***Manual inspection of food products:*** This technique entails human intervention for the manual assessment of food products to identify quality. Experts with domain knowledge independently evaluate each adulterant and characterize their properties. Manual inspection relies on factors like the physical appearance of the food, its aroma, texture, and other relevant parameters. Nonetheless, even these experts may sometimes encounter challenges in making accurate determinations.
- ***Observation-based methods to detect food quality:*** Various observational methods are employed at home and in small-scale settings to detect contaminants in food items. For instance, a drop of milk is placed on a polished slanting surface to ascertain the presence of water in milk. If the milk leaves a trace behind as it flows, it is considered pure; in the case of contaminated milk, it flows without leaving any mark. Similarly, the oil is refrigerated in a transparent glass to identify other oils mixed with coconut oil. Coconut oil solidifies, while other oils form a distinct layer in the glass. Numerous other methods, such as heating and dissolving samples in water, are utilized to detect adulterants in various food products.

Challenges of Conventional Methods of Food Quality Detection

Researchers have investigated and found that automated systems sometimes outperform human assessments in discerning food quality. Automated systems possess significant potential in assessing the quality of diverse food products. In contrast, traditional methods are intricate and labour-intensive, potentially leading to delays, as mentioned earlier. Moreover, precise analysis necessitates specialized infrastructure. Additionally, the verification and validation of results demand involvement from various agencies. These methods are time-consuming, intricate, and inefficient. The present methods of identifying possible contaminants burden domain experts who may lack the necessary resources and capabilities. Consequently, to enhance these techniques and their precision, artificial intelligence (AI) emerges as a solution, deploying distinct approaches to detect food quality.

2.4.2 AI Based Food Quality Detection Techniques

AI has been playing a predominant role in food safety and quality assurance. The food industry has been leveraging the advantages of the latest advancements in AI. Product inspection in the food industry is in high demand, including quality inspection of the food products, classification, and grading of fruits and vegetables.

The data required for analysis can be in two forms to build an AI system to detect food quality. The first type of data is used to develop a vision-based model. The main focus is to inspect the quality of food items based on parameters like colour, texture, size, shape, defects, morphological features, *etc*. The classification is done based on the physical appearance of the fruits, vegetables, and dairy products by training the data using ML models. The second data type consists of parameters such as moisture, pH, temperature, pressure, humidity, viscosity, and other related parameters that aim to examine the chemical composition of the food products. For this purpose, the Internet of Things (IoT) can be used to collect data from different sensors, and the decision of quality detection is made based on the contents of the food products. Other modern types of equipment, like electronic tongue and electronic nose receive such data and perform analysis to evaluate the food quality.

a. Vision-Based Methods

The visual aspect is a pivotal parameter in evaluating food quality. Using vision-based models involves employing images of food products to detect quality by training visual datasets on ML and DL models. These models are also adept at assessing food quality based on textual data. Computer vision systems are harnessed for the automated and accurate classification of food items, contingent on their adulteration levels. Food quality evaluation can be executed by capturing data through a digital camera and then utilizing ML models for predictive purposes. Artificial Neural Networks (ANN) have gained considerable prominence in recent research endeavors due to their capacity to autonomously learn features from data with minimal prior knowledge and independent feature selection. These networks draw inspiration from the functioning of the human neural system, acting akin to a black box that adjusts weights based on training rules. Neural networks find utility in scenarios where the exact model is unknown. They utilize the constituents of food products to train, utilizing images to extract textural, shape, and morphological properties. The successful implementation of ANN classifiers offers the potential to inspect food product quality and facilitate grading processes. The Figure 2.5 depicts the automated methods used for food quality detection. It showcases a collection of various portable devices that seem to be used for analyzing different food items and materials. A hand-held scanner being used on a variety of food items alongside an app on a smartphone that displays "Food Scanner". This is a device used for determining food composition, nutritional facts, or allergen information. These devices collectively seem focused on health, nutrition analysis, and are likely aimed at consumers seeking more information about the products they use or consume, or professionals needing portable diagnostic tools in the field.

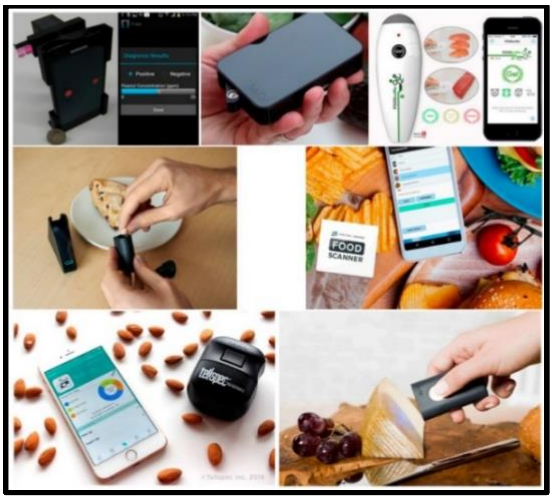


Figure 2.5. Automated Methods to Detect Food Quality [47]

A Convolutional Neural Network (CNN) architecture can be suggested, possessing the ability to extract features necessary for detecting food quality. The vision-based approach is considered environmentally friendly, as it circumvents the requirement for chemical reagents. This method offers numerous other benefits, including prompt and practical outcomes, cost-effectiveness, and extensive applicability within the food industry for tasks like classification and grading. In response to research question RQ3, i.e., “What are different techniques followed to detect food quality?”, a comprehensive breakdown of the vision-based techniques employed by researchers is delineated in Table 2.4.

Table 2.4. Summarized review of Food Quality Detection System using vision-based methods

Author(s)	Proposed Methodology	Techniques and Dataset	Conclusion
Pourreza et al. (2011) [48]	The grayscale images of wheat seeds were studied to extract 131 textural features. LDA classifier has been employed to select top features for classification.	LDA and Textural Feature Extraction Matrices (GLCM, GLRM, LBP, LSP, LSN). 1080 grayscale images of 9 wheat seeds qualities (120 images of each variety)	accuracy: 98.15%, where best results were given by LSP, LSN, LBP
Neelamegam et al. (2013) [49]	Image processing was used to differentiate basmati rice from other inferior qualities of rice	Feature extraction using Neural networks and digital imaging. Filters such as grayscale, median smoothening, canny edge detection, adaptive thresholding, Sobel edge detection, and morphological operations using a computer vision library of functions to preprocess the images.	The results obtained improved crop recognition and reduced the time of operations to a great extent.

Author(s)	**Proposed Methodology**	**Techniques and Dataset**	**Conclusion**
Nandi et al.(2014) [50]	Automatic grading system for mango using computer vision	A CCD camera positioned above a mango-carrying conveyor belt is used to acquire video images. Finally, a fuzzy rule-based algorithm is utilized to classify the fruits into four categories	Classification performed well
Carolina et al. (2014) [51]	The classification was done based on the degree of maturity of oranges using their physical characteristics.	Image Processing	The oranges were classified based on their maturity level.
Ropodi et al. (2014) [52]	Multispectral imaging identifies intentional adulteration in minced beef with pork and vice versa.	The dataset comprised images captured at 18 distinct wavelengths, encompassing 220 meat samples across four experiments, each involving 55 samples. The nine different proportions were prepared by mixing beef and pork-minced meat was mixed. PLS-DA and LDA have been used.	Classification Accuracy: 98.48%

Author(s)	**Proposed Methodology**	**Techniques and Dataset**	**Conclusion**
Khosa et al. (2014) [53]	ANN classifier has been employed for quality evaluation. GLCM extracted six texture properties and sixteen features at 0, 45, 90, and 135 angles.	ANN and PCA are used with a dataset consisting of images.	The parameters like accuracy, sensitivity, and specificity were calculated for extracted features.
Kamruzzaman et al. (2015) [54]	Adulteration of minced beef with chicken was detected by hyperspectral imaging at three different profiles.	Partial least squares regression (PLSR)	($\hat{R}^2$) = 0.97, 0.97, and 0.96 and RMSEP of 2.62, 2.45, and 3.18%.
Ali et al. (2017) [53] [55]	Fraudulent labelling of rice samples was detected using computer vision and fuzzy knowledge.	Neural network	Precision: 90% high accuracy
Lim et al. (2017) [54] [56]	mass spectroscopy combined with supervised ML algorithms was used to detect adulterated mixtures of white rice.	RF, SVM, DT, ANN, and KNN were used. The dataset consisted of 330 samples of white rice mixed in seven different ratios.	RF and SVM outperformed other classification techniques.

Author(s)	**Proposed Methodology**	**Techniques and Dataset**	**Conclusion**
Kobek et al. (2017) [57]	The images of the milk samples skimmed with bromothymol blue (pH indicator) were captured. The neural network was trained, and the image was classified using colour parameters red (R), green (G), blue (B), and luminosity.	ANN, PLSR, and principal component regression analysis (PCR) model	The model proposed was used to identify the milk adulteration.
Fayyazi et al. (2017) [58]	Image processing and MLP Neural Networks were used to identify and classify three rice varieties, where 17 morphological and 41 textural features were extracted from the pictures of the seeds.	PCA for feature ranking and MLP for classification were used, and 666 images of rice seeds were considered, with 222 images of each type.	classification accuracy Type 1: 55.93%, Type 2: 84.62% Type 382.86 % In the testing phase, the accuracy was calculated using rice varieties once a time.
Rong et al. (2017) [59]	Detection of the surface defects in the oranges in grey-level images.	Techniques like window local segmentation algorithm and image processing were used, and the dataset comprised 1191 images.	The defects of the oranges were identified using the image processing and window local segmentation algorithm.

Author(s)	Proposed Methodology	Techniques and Dataset	Conclusion
S. Anami et al. (2018) [60]	The 7 different samples of paddy are prepared by using a mixture of high-quality paddy with identical low-quality and different adulteration ratios (	Classification methods like BPNN, SVM, and k-NN and feature selection methods like PCA and Sequential Forward Floating Selection (SFFS) methods were used.	An automated method to recognize and classify the adulteration levels from the samples of paddy grains.
Tripathy et al. (2018) [61]	A paper-based approach is utilized to identify milk adulteration using sensors showcasing three distinct colors	pH-based sensors and SVM	The pH strips are made and are used to detect milk adulteration
Al Sarayreh et al. (2018) [62]	The SVM model to detect adulteration in red meat products and investigate the handcrafted spectral and spatial features and CNN for self-extraction spectral and spatial features.	Methods such as Hyperspectral imaging employing CNN and SVM Models are utilized, and a dataset comprising images of lamb, beef, or pork muscles is gathered.	CNN model accuracy: 4.4%
Neto et al. (2019) [63]	CNN architecture to recognize FTIR data collected from infrared spectroscopy to use deep and ensemble learning methods to identify milk adulteration.	Infrared spectroscopy and ML algorithms, such as deep and ensemble DT learners	classification accuracy: 98.76%

Author(s)	**Proposed Methodology**	**Techniques and Dataset**	**Conclusion**
Izquierdo et al. (2019) [64]	Deep learning was used to classify the five varieties of rice.	CNN	Accuracy=93.4%
Jahanbakhshi et al.(2021) [65]	Detection of chickpeas powder in turmeric powder	CNN	Accuracy: 99.36%
Fatima et al. (2021)[66]	Detection of Papaya Seeds in black peppercorns	SNN	Training Accuracy: 96% Validation Accuracy: 92%
Menaka et al.(2021) [67]	Identification of quality of rice grains using digital imaging	BPNN, MLP, and SVM	Proposed Method: 98.4% SVM: 92%
Mandal et al.(2021) [68]	Detection of the presence and amount of Metanil yellow (MET)	Deep Learning and Random Forest Regression	Accuracy: 98%
Rady et al.(2021)[69]	Utilization of color imaging and ML to detect adulteration in minced meat	LDA	Accuracy: 76.3–99.1%,
Lopez et al.(2022) [70]	Milk Classification by adulterating melamine	ResNet34	Accuracy:98.7%
Phillips et al.(2022)[71]	Hyperspectral imaging to detect adulteration in Honey	Machine Learning	Accuracy binary Classification: 95%

Author(s)	**Proposed Methodology**	**Techniques and Dataset**	**Conclusion**
Zhou et al.(2022)[72]	NIR-based DL approach to detect powder identification in food	12 categories detection	Accuracy: 97.86%
Geng et al.(2022) [73]	Microscopic imaging method to identify adulteration in fishmeal	YOLOv3	*mAP:*78.49%, *FPS:*$45.97\, f{\cdot}s^{-1}$
Fan et al.(2022)[74]	Hyperspectral Imaging combined with ML to detect mutton adulteration	BPNN, ELM, SVM	99.79% R_P^2 of 0.9304 and an RMSEP of 0.0458
Hu et al.(2023)[75]	Detection of adulteration of Tieguanyin	Hyperspectral imaging in fusion with ML algorithms	R_p^2 values ranging from 0.9804 to 0.9831.
Kaushal et al.(2023)[76]	Adulteration detection in Khoa using UV spectroscopy	Adulterants usually spiked with milk are the same for khoya, such as starch, detergent, hydrogen peroxide, colostrum	The research focused on UV spectroscopy in adulteration detection
Dogan et al.(2023) [77]	Image Processing to detect adulteration of Pistachio images	DT, RF, kNN, SVN, NB, ANN	*Accuracy ANN:* 93.65%, 0.87 of Matthews correlation coefficient (MCC)

Author(s)	Proposed Methodology	Techniques and Dataset	Conclusion
Ojeda et al.(2023) [78]	Classification of mayonnaise using various extracted features by ML Models.	SVM, Gradient Boosting, and KNN models	Accuracy: 88.33, Precision: 94.37, Recall: 93.54, F1-measure: 93.75%
Wojcik et al.(2023) [79]	Computer Vision Method for honey adulteration detection	PCR, PLSR, SVR	$R^{2=}99.98$

Some researchers have harnessed machine learning techniques to assess the quality of food based on textual data. They have extracted features in a CSV file. The dataset encompasses various parameters associated with the food product. Most researchers have employed Artificial Neural Networks (ANN) to execute food quality detection. The methodologies used in the literature survey are briefly described in Table 2.5.

Table 2.5. Summary of work in the area of Food Quality Detection using Textual data

Author(s)	Proposed Methodology	Techniques and Dataset	Conclusion
Li et al. (2009) [80]	The sour skin of onions was detected using SVM and gas sensor array. PCA method was used to show the distinct clusters formed by healthy and infected onions. Hypothesis testing was done using MANOVA to check the p values.	SVM and PCA for classification. MANOVA for hypothesis testing	Accuracy: 85% for validation and 81% during training. p-value < 0.0001 concluded that the two types of onions were considerably different.
B.Debska et al. (2011) [81]	ANN method was used to classify beer samples into two classes	ANN with 70 beer samples, and 12 features were used.	Classification Accuracy: almost 100%

Author(s)	Proposed Methodology	Techniques and Dataset	Conclusion
Meire et al. (2013) [82]	Authentication of samples of wine was done by collecting from 6 different origins using ML Techniques.	SVM, RF, Multilayer Perceptron, k-NN, and Naive Bayes were used. The dataset comprised 42 samples of grapes.	Best accuracy: Random Forest
Bandyopadhyaya et al. (2014) [83]	To check the ripeness of tomato and ladyfinger by a touch-sensitive robotic system using machine learning	SVM, KNN	Tomato classification: SVM: 64.23% KNN: 92.86% Lady Finger classification: SVM: 60% KNN: 80%
Dan Peng et al. (2015) [84]	Gas chromatography and multivariate data analysis were used to identify the adulteration of sesame oil with vegetable oils.	SVM and PLSM are used, and a mixture of five types of vegetable oils was used on 746 samples.	RMSEP value ranged from 19% to 4.29%
Mu et al. (2015) [85]	A partial least square model was built to predict the adulteration concentration with errors lower than 2 %. Then, ANN and SVM were used to classify pure and mixed oils.	Multivariate Analysis using laser-induced fluorescence (LIF), ANN, and SVM was used where the dataset comprised 280 sets classified into four groups (including olive, rapeseed, peanut, and blend oils).	Pure oils are differentiated from a mixed oil well.
Rashvand et al. (2016) [86]	Adulteration detection using dielectric technique and data mining from the samples of olive oil, sunflower oil, and canola oil mixed in different ratios.	(LDA) in combination with the dielectric-based system, a dataset of 15 samples was used.	The highest error rate is 60% olive oil and 40% canola oil. Specificity: 98%, Sensitivity: 99% accuracy: 72%.

Author(s)	**Proposed Methodology**	**Techniques and Dataset**	**Conclusion**
Yu et al. (2017) [87]	Identification of wine from grape varieties using NIR spectroscopy combined with RBFNN and (LS-SVMs) based on PCA.	NIR spectroscopy combined RBFNN and LS-SVM based on PCA.	The accuracy of RBFNN varied from 90.16% to 98.36%. RBF LS-SVM, identification rates were in the range of 91.80 % - 98.36%.
Zhang et al. (2018) [88]	Use of machine learning to predict the quality risks of dairy products.	ELM and K-ELM were used to construct a waring model to evaluate the quality risk of dairy products.	K-ELM performed the best in food safety regarding accuracy and training time.
Santana et al. (2018) [89]	Adulteration Detection from primrose oils and ground nutmeg using the random forest in combination with infrared spectroscopy.	Adulteration of primrose oil using corn, sunflower, and soybean oils. In the case of ground nutmeg, adulterants included cumin, commercial monosodium glutamate, soil, roasted coffee husks, and wood sawdust.	Regarding primrose oil, the proposed method performed better than PLS-DA and was comparable to SIMCA. On the other hand, for ground nutmeg, random forest outperformed PLS-DA and SIMCA.
Naskar et al. (2018) [90]	Detection of grapefruit juice adulterated with sugar solution and water	PCA, Box Plot, and LDA	Separability Index (SI) identified adulteration like sugar solution and water in pure grape juice.

Author(s)	**Proposed Methodology**	**Techniques and Dataset**	**Conclusion**
Iymen et al.(2020) [91]	Utilization of sound vibrations to identify adulteration in butter	AI	The models CNN-RNN and CRNN achieve high accuracy
Farah et al.(2021) [92]	ML approach to detect the authenticity of milk	RF, GBM, MLP	RF performed best with 100% recognition and 88.5% prediction results
Piras et al.(2021) [93]	Detection of adulteration in milk using ML	Cow, Goat, sheep, camel Milk Detection of Cow milk in goat milk	Classification Accuracy:100% 92.5% sensitivity and 94.5% specificity
Zhao et al.(2022) [94]	Raman Spectroscopy, in combination with ML, is used to detect adulteration in edible oil	Nine supervised ML algorithms	Accuracy: 96.7% R^2= 98.4
Chung et al.(2022) [95]	An ensemble machine learning approach for the identification of unprecedented food adulteration.	Non-targeted detection of raw milk without prior knowledge of adulterants in the milk	Accuracy: 99.24% F1 Score: 99.13%
Hemamalini et al.(2022)[96]	Food quality Assessment using image segmentation and Learning	KNN, SVM, C4.5	Binary Classification
Sarkar et al.(2023) [97]	Detection of red brick powder within red chilli powder blended at varying proportions.	Cat Boost classifier, Extra Tree regressor	Best Results for Classification by Cat Boost classifier with HSV color space and for Regression Extra Tree regressor with Lab color space histogram features

Author(s)	**Proposed Methodology**	**Techniques and Dataset**	**Conclusion**
Sitorus et al.(2023)[98]	Identification of adulteration of nutmeg with cinnamon	NIR Spectra with ML models PC-MLP, PC-LDA, PLSR, SVM, RF, DT	R^2_{pred}: 0.9969, RMSEP: 0.5728%, ratio of prediction to deviation (RPD) value 17.9605.
Lanjewar et al.(2023) [99]	Detection of starch in Turmeric mixed in various proportions	RF, DT and KNN were used as base learners, and LRC was used as a meta-model for classification and LR was used for regression .	Best results with regression where r^2 of 0.999, Root Mean Square Error (RMSE) of 0.206

b. IoT-Based Food Quality Detection Methods

Integrating AI and IoT has emerged as a robust framework to ensure food security and safety. IoT technology can be harnessed to transform the quality detection system into an intelligent device. This technology could seamlessly integrate into the food supply chain to elevate food quality, monitor conditions, and share real-time data with consumers. As depicted in Figure 2.6, the system operates across three key phases: (i) Sensing, (ii) Analysis, and (iii) Prediction.

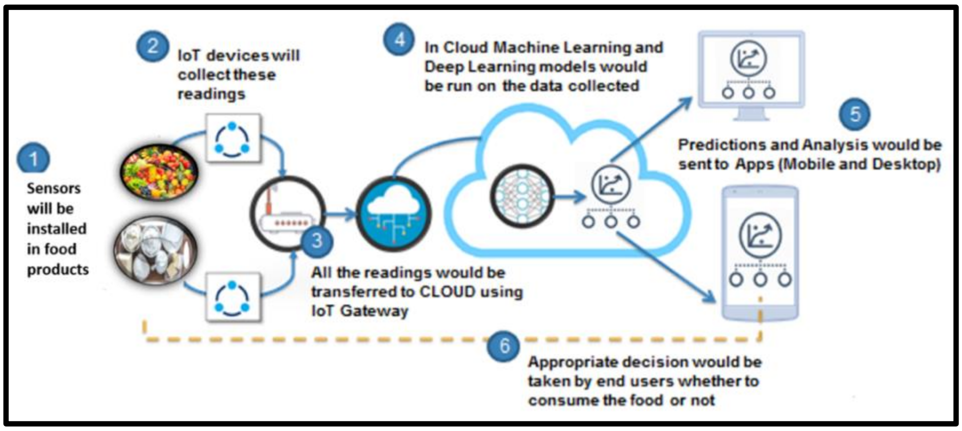


Figure 2.6. Working of IoT System

The food quality system is devised to monitor diverse environmental factors—such as temperature, humidity, alcohol content, and light exposure—that could impact food decay. The system's ability to discern food quality is a foundation for the monitoring system. The compilation of pertinent IoT research for food quality assessment is concisely outlined in Table 2.6.

Table 2.6. Summarized work in the domain of Food Quality Detection System using IoT

Author(s)	Proposed Methodology	Techniques and Dataset	Conclusion
Jia et al. (2011) [100]	A method to create a quality monitoring platform for food production using IoT. The approach incorporates RFID tags and 1-D code, establishing techniques to model food quality.	IoT and RFID Tags	A food quality supervision system is set up.
Eom et al. (2012) [101]	Vegetable freshness has been assessed by introducing a monitoring system that utilized radio RFID to measure oxygen and carbon dioxide concentrations.	Sensors are used to measure oxygen and carbon dioxide levels using RFID tags.	The concentrations of these gases were monitored.
Chanthini.Bet al. (2017) [102]	The concept of IoT was used to monitor the quality of perishable food from a remote location. The use of Raspberry pie as a sensor node and a gateway node to provide data collected from different sensors like temperature, humidity, and moisture.	IoT	A system to monitor food quality using IoT was developed.

Author(s)	**Proposed Methodology**	**Techniques and Dataset**	**Conclusion**
Gupta et al. (2018) [103]	The poor quality of the food was detected using different sensors that were used to record the data and Raspberry Pi to control the entire working of the system.	Internet of Things	A food adulteration monitoring system was developed.
Kang et al. (2019) [20]	Apple Segmentation and Detection in real-time employing Visual Sensors with ResNet 101.	The developed detection and segmentation network leverages atrous spatial pyramid pooling and the gate feature pyramid network to augment the network's feature extraction capabilities.	ResNet-101 outperformed on the detection and segmentation tasks with F1 score of 0.832 and 87.6% and 77.2% on the semantic case .
Tsang et al.(2019) [104]	Integration of blockchain with IoT to detect food quality	IoT, Blockchain, Fuzzy Logic	Well Blockchain integration with IoT
Kaya et al.(2020) [105]	ML-based model to tolerate failed sensor for food quality prediction	Single Plurality Voting System (SPVS), KNN, DT, LDA	Promising results for beef cut quality assessment
Alfian et al.(2020) [106]	Utilization of RFID and IoT to detect the quality of perishable food	IoT sensors to track temperature and humidity during transportation	Successful integration of RFID and IoT for Food Quality detection
Sowmya et al. (2021) [107]	IoT based Spectroscopic system to detect real-time milk adulteration	DT, NB, LDA, SVM, NN	Accuracy LDA:88.1%, SVM: 90%, NB: 90%, DT: 91.7%, NN: 92.7%

Author(s)	Proposed Methodology	Techniques and Dataset	Conclusion
Thangamayan et al. (2022) [108]	Blockchain-based food tracking system	IoT	Blockchain in food traceability has multiple advantages
Anbalagan et al. (2022) [109]	IoT-based coconut oil adulteration detection system using optic fiber sensor	Adulteration of paraffin oil in coconut oil	The sensor is capable of monitoring the distant sensor

c. Quality Control of Food Using Electronic Methods

The Electronic Nose (E-Nose) and Electronic Tongue (E-Tongue) are devices designed to mimic the functions of the human nose and taste buds. They consist of an array of sensors. These devices find extensive applications in detecting food quality. The intricate datasets produced by E-Nose and E-Tongue signals, combined with multivariate statistical analysis, serve as rapid and effective tools for classifying, distinguishing, recognizing, and identifying samples. Moreover, they can predict the levels of various compounds.

An Electric Nose surpasses the human sense of smell in detecting odors. It gathers information about the characteristics of the substances being examined through chemical detection principles. This intelligent sensing tool employs an array of gas sensors that overlap in their response patterns. When the sensor system of the E-Nose interacts with volatile compounds, it changes electrical properties. The resulting specific responses are then translated into digital values [6]. Statistical models are applied to the recorded data for computation. This technology finds widespread use in research, particularly in identifying harmful gases present in contaminated food, which the human nose cannot accomplish.

The Electronic Tongue (E-Tongue) serves as a multi-channel taste sensor employed for identifying, categorizing, and quantifying constituents within liquid samples. Information about the samples is gathered by sensors designed to imitate the function of gustatory cells found in the tongue's taste buds. This ensemble of specific sensors captures a digital representation of the sample, transmitting details regarding taste-related compounds into electrical signals. These signals then serve as input profiles for the data recognition system.

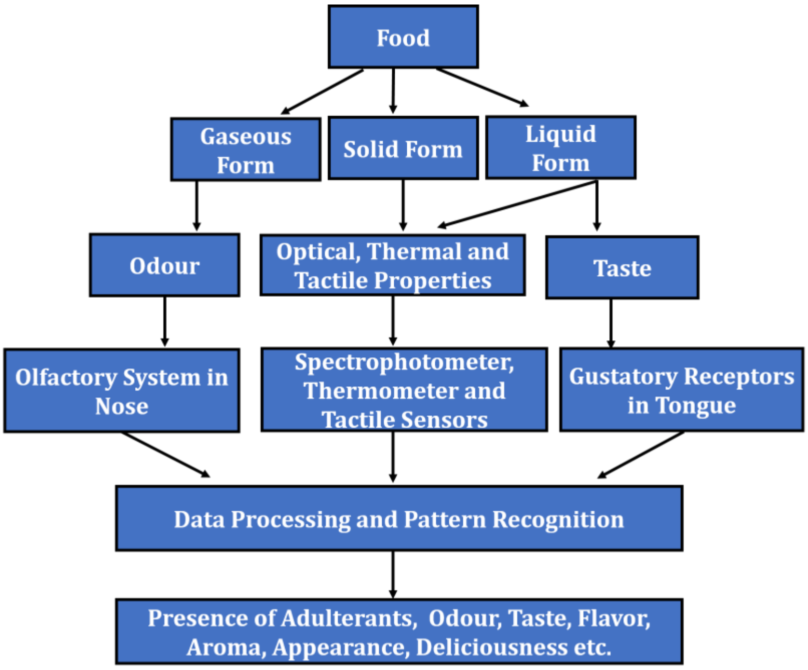


Figure 2.7. The architecture of E-Nose and E-Tongue

Figure 2.7 illustrates the operational framework of both the E-Nose and E-Tongue, showcasing that food products can be examined in three states: solid (e.g., fruits, vegetables), liquid (e.g., milk, juices), and gaseous (volatile compounds emitted from products). Solid materials are evaluated through factors such as texture, shape, color, thermal properties, and optical characteristics. In the case of liquids, the taste of the food is scrutinized, while for gases, judgment is based on odor and the volatile compounds released by the substances. These electronic devices replicate the olfactory system of the nose to study gaseous components and mimic gustatory receptors in the tongue to analyze liquid compounds.

Sensory devices like spectrophotometers and thermometers are employed for analyzing solid products. Additionally, Machine Learning (ML) and Deep Learning (DL) models can be utilized for classification and pattern recognition. These models aid in predicting the presence of adulterants in food. Furthermore, the model's predictions can analyze parameters like odour, taste, flavour, appearance, and food texture. A comprehensive overview of the research associated with these electronic methods is detailed in Table 2.7.

Table 2.7. Overview of food quality detection system using E-Nose and E- Tongue

Author(s)	**Proposed Methodology**	**Techniques and Dataset**	**Conclusion**
Markom et al. (2009) [110]	The samples of odour were taken on the site of the plant, and the system was capable of distinguishing between the healthy and infected palm tree using different odour parameters such as the odour of the surrounding tree, the odour of the bored trunk, and the odour of soil.	Cyranose 320	The classification has been performed well.
Kundu et al. (2010) [111]	Machine learning algorithms are employed to classify unknown water samples, and data acquisition is facilitated using E-Tongue technology	PCA and partial least squares (PLS), E-Tongue are used. The dataset consisted of 6 classes of samples with 4402 features.	The water samples were classified into 6 classes.
Subari et al. (2012) [112]	Testing involves 10 distinct certified pure honey brands, and samples are generated with various adulteration concentrations (20%, 40%, 60%, and 80%) using two types of sugar solutions (cane sugar and beet).	LDA and PCA were used. Data Collection using E-Nose and FTIR	The accuracy of FTIR-based data is 88%, and for E-Nose data was 76.5%

Author(s)	**Proposed Methodology**	**Techniques and Dataset**	**Conclusion**
Teye et al. (2013) [113]	Cocoa bean identification is conducted utilizing E-Tongue technology and pattern recognition methods.	Pattern Recognition techniques such as Fisher's discriminant analysis (FDA), PCA, KNN, and SVM are employed, and data acquisition was facilitated using E-Tongue.	SVM achieved the best results
Heidarbeigi et al. (2015) [114]	E-Nose was used to find the different types of adulterants in the saffron samples. The aroma fingerprints of saffron, saffron with yellow styles, safflower, and dyed corn stigma were detected by an E-Nose system.	Backpropagation and ANN were used for classification, and the PCA method was used for feature reduction.	Accuracy: 86.87%[115]
Bougrini et al. (2016) [115]	The samples of honey were classified and analyzed using three pattern recognition techniques. For adulterant detection, these adulterants were with authentic honey with ratios 2, 5, 10, and 20% by weight, respectively.	E-Tongue for data collection and pattern recognition techniques: PCA, SVMs, and HCA are used. The dataset consisted of 18 and 7 honey varieties based on geographical and botanical origins.	Excellent classification results were achieved.

Author(s)	**Proposed Methodology**	**Techniques and Dataset**	**Conclusion**
Ordukaya et al. (2017) [116]	Quality control of olive oil using ML and E-Nose. In the first technique, 32 inputs were applied to the classifiers, and in the second method, PCA was used to minimize the 32 to 8 inputs.	Naive Bayesian, *k*-NN, LDA, DT, ANN, and SVM	The second method produced better results than the first one, with the best accuracy achieved in the case of the NB classifier at 70.83%.
Ayari et al. (2018) [117]	Cow ghee was analyzed for adulteration using an E-Nose to identify sunflower oil and cow body fat mixed with pure cow ghee in different ratios.	PCA and ANN	PCA Accuracy: sunflower oil: 96% Cow body fat:97% ANN accuracy: sunflower oil: 91.3% Cow body fat: 82.5%
Tian et al. (2019) [118]	A combination of E-Nose and E-Tongue was used to detect the adulteration of minced mutton mixed with pork.	For Normalization, LDA and PCA and for regression, MLR, PLS, and BPNN were used.	R^2= 0.97 for BPNN
Poghossisan et al.(2019)[119]	Milk spoilage detection using chemical and biosensors	VoC compounds detection, pH, conductivity	ENose and E Tongue for milk spoilage detection
Rasekh et al(2021)[120]	Classification of volatile oil from herbs and E-Nose	PCA, LDA and QDA, and SVM	Accuracy: 100%
Rasekh et al.(2021) [121]	ENose to detect juice quality	ANN	MQ135 and TGS813 sensors are the most powerful, and MQ9 and MQ3 sensors are the least powerful in the classification of different types of fruit juices

Author(s)	Proposed Methodology	Techniques and Dataset	Conclusion
Tatli et al.(2021) [122]	Utilization of Enose to detect urea from cucumber	ANN, SVM, LDA-QDA	ANN= 96.7% C-SVM= 94% QDA= 92% LDA= 98.67%
Han et al.(2022) [123]	ENose and gas chromatography to detect adulteration in edible oils	LDA, PLS	PLS model based on Gas chromatography-ion mobility spectrometry (GC-IMS) data led to adequate differentiation of adulteration rates in safflower seed oil (SSO)
Huang et al.(2022)[124]	Meat Adulteration Detection using Enose	BPNN, DCNN, RFR	Best Results DCNN-RFR
Tian et al.(2023) [125]	Vegetable oil adulteration detection using Enose in milk	RF, SVM	Accuracy: 100% and 95.65% F1-scores: 96.25 and 97.78
Goncalves et al.(2023)[126]	Adulteration Detection of honey using E-nose	(J48), random forest (RF), multilayer perceptron (MLP), naive Bayes (NB), and sequential minimal optimization (SMO).	Accuracy: 100%

Author(s)	**Proposed Methodology**	**Techniques and Dataset**	**Conclusion**
Kang et al.(2023)[127]	Tea Quality determination using E-Nose	CNN, Adaptive pooling attention mechanism	Accuracy: 97.62%, precision of 97.57%, recall of 97.71%, and F_1-score of 97.64%,
Binson et al.(2023)[128]	Low Cost portable ENose using MOS sensors to detect the freshness of beef	SVM	accuracy, sensitivity, and specificity of 91.5%, 91.08%, 90.90%
Wu et al.(2023) [129]	film bulk acoustic resonator (FBAR)-based E-nose to measure the shelf life of the bananas	Gas sensor	Easy detection of bananas
Medina et al.(2023)[130]	Classification of Honey using E Tongue	KNN	Accuracy: 100%

Therefore, it becomes essential to employ IoT devices for data sensing and ML models for making predictions using the gathered data to construct a technology-driven system for detecting food quality.

2.5 Machine Learning and Deep Learning Applications in the Food Industry

Machine Learning (ML) constitutes a subset of artificial intelligence, wherein computers acquire knowledge and make decisions without explicit programming. It involves crafting algorithms capable of learning from data and making predictions based on that data. Machine learning is divided into two main categories: supervised and unsupervised. Food items are pre-assigned to classes in supervised learning, and training data is available for each class. The trained model is employed to predict and categorize food products. In unsupervised machine learning, models lack labeled data.

Deep Learning, which falls under the umbrella of machine learning, emulates human brain functions and is celebrated for its powerful pattern recognition capabilities. Utilizing deep neural networks with multiple layers of neurons offers the advantage of automatic feature engineering and high accuracy, making it effective even for intricate issues.

In recent years, there's been a notable trend towards machine vision within the food industry. This trend has seen substantial growth in both theory and practical implementation.

The answer to RQ4, i.e., "What are the various applications of deep learning and machine learning in the field of food?" is discussed below.

- Food Recognition and Classification
- Food Calorie Estimation
- Food Supply Chain
- Quality Detection of Fruits and Vegetables

The details of these applications are elaborated in the following subsections.

2.5.1 Food Recognition and Classification

Dietary habits and daily consumption are pivotal in individuals' overall health. Recognizing and categorizing food items is fundamental, enabling people to document their everyday diets. This task is of utmost importance for individuals managing diabetes and allergies, as they must diligently monitor and regulate their dietary choices. Information about food products is often encapsulated within their images. Employing images for data acquisition is a straightforward and cost-effective approach to food recognition and categorization. However, this task becomes intricate when dealing with natural products that exhibit size, shape, volume, texture, color, and composition variations. Varied backgrounds and arrangements of food items further compound the challenges in food classification and recognition. Due to the widespread utilization of Convolutional Neural Networks (CNNs), image analysis has emerged as the predominant approach for food recognition and classification.

Numerous machine learning and deep learning techniques are available for this purpose. Yet, CNN architectures stand out for image identification. Among these structures are AlexNet [131], which introduced the concept of deep learning to image recognition; The VGG (Visual Geometry Group) network [132] is recognized for its repetitive units; GoogLeNet [133], is distinguished by its parallel data channels; and ResNet (He, Zhang, Ren, & Sun, 2016), is structured using residual blocks. Furthermore, these network architectures can be easily accessed from model repositories, including pre-trained weights. These pre-trained models have been trained on extensive image datasets such as ImageNet [134], enabling them to effectively extract vital image features like colors, texture information, and high-level abstract representations[135]. Researchers can then employ their specific image datasets to transfer learning based on these pre-trained models. It entails fine-tuning the weights of a fully connected structure for final classification, while keeping the weights of the convolutional layers unaltered or making slight adjustments to the entire network's weights. A compendium of researchers contributing to food recognition and classification can be found in Table 2.8.

Table 2.8. Summary of the work in the field of Food Recognition and Classification

Author(s)	**Model**	**Dataset**	**Results**
Rocha et al. (2009) [135]	Automatic fruit and vegetable classification using a combination of features.	Supermarket Produce Dataset available online	High classification results with SVM
Bossard et al. (2014) [12]	Machine Learning Methods	Food-101 database	Accuracy: 50.76%
Yanai et al. (2015) [23]	fine-tuned AlexNet	Food-101 database	Top-1% Accuracy: 70.41%.
Heravi et al. (2015) [30]	The modified version of AlexNet	dataset included 1316 images in 13 food categories	Accuracy: 95%
Ragusa et al. (2016) [136]	AlexNet, in combination with a binary SVM classification model	The dataset included images from Flickr with nonfood and food images and 3583 food images from UNICT-FD889.	Accuracy: 94.86%
Shimoda et al. (2016) [137]	CNN VGG -16	UECFOOD-100	High classification accuracy
Tatsuma et al. (2016) [137], [138]	covariances of features of trained CNN	Food-101 database	Accuracy: 58.65%
Liu et al. (2016a) [26]	Deep Food Network	Food-101 database	Accuracy Top-1%: 77.40% Top-5% : 93.70%

Author(s)	**Model**	**Dataset**	**Results**
Herruzo et al. (2016) [26], [139]	GoogLeNet	FoodCAT was presented based on Catalan food. Food-101	Food Identification Accuracy: Top-1%:68.07% Top-5%: 89.53% Food categories Recognition Accuracy: Top-1%:72.29% Top-5%:97.07%).
Fu, Chen, and Li (2017) [28]	fine-tuned deep 50-layer ResNet.	Food-101 database	Accuracy Top-1%: 78.5% Top-5% : 94.1%
Mezgec and Seljak (2017) [140]	The modified AlexNet model was used to develop a system named NutriNet	Training dataset: 225953 images of food and drink items Testing images: 130517	Classification accuracy: Training: 86.72% Testing: 94.47%
Fu et al. (2017) [28]	ResNet architecture	ChinFood1000 database	Accuracy Top-1%: 44.10% Top-5%: 68.40%.
Pandey et al. (2017) [27]	multilayered CNN that used AlexNet architecture	Food-101 dataset and Indian food database that consisted of 50 categories with 100 images of each	Accuracy for Food-101 Top-1%: 72.12% Top-5% : 91.61% Top-10%: 95.95% Accuracy for Indian Food Dataset Top-1%: 73.5% Top-5% : 94.4% Top-10%: 97.6%
Ciocca et al. (2018) [31]	ResNet-50 model	Food-527, Food-475, Food-50, and VIREO	High classification accuracy

Author(s)	Model	Dataset	Results
W. Jia et al. (2018) [10]	GoogLeNet model for Binary Classification.	Food-5K database	Accuracy: 99.2%
McAllister et al. (2018) [42]	Using ResNet-152 combined with a Radial Basis Function (RBF) kernel-based SVM.	Food-5K database	Achieving an accuracy of 99.4% for the validation dataset and 98.8% for the evaluation dataset.
Martinel et al. (2018) [33]	CNN architecture named WISeR, where they initially developed a slice convolution unit to extract shared vertical food features. Subsequently, deep residual blocks were incorporated to form a composite structure for computing the classification score.	Food-101, UECFood-256 and UECFood-100	Accuracy for Food-101 Top-1%: 90.27% Top-5% : 98.71% Accuracy for UECFood-256 Top-1%: 83.15% Top-5% : 95.45% Accuracy for UECFood-100 Top-1%: 89.58% Top-5% : 99.23%
Khaing et al. (2018) [141]	CNN	The dataset consisted of 971 images.	Accuracy: 94%
Rong et al.(2019) [59]	Detection of foreign objects in walnuts using deep learning	Walnut image database with 101 test images and 277 validation images	Accuracy: 95%
Li et al.(2019) [142]	DL method for recognition and classification of vegetables	VGG network and AlexNet network	Accuracy: 96.5% VGG network (92.1%) and AlexNet network (86.3%

Author(s)	**Model**	**Dataset**	**Results**
Bhole et al.(2020) [143]	Mango sorting and grading system using DL	RGB and Thermal images	Accuracy:93.33%
Helwan et. al(2021)[144]	DL-based Automated Banana Sorting System	Res Net Banana Image Dataset	Accuracy: 99%
Patil et al.(2021) [145]	Grading and sorting of dragon fruits using raspberry pie and machine learning	CNN, ANN, SVM	Dragon fruit was classified based on maturity
Melesse et al.(2022)[146]	Usage of thermal imaging technique in combination with ML to monitor banana quality	Thermal dataset with 4 classes	Accuracy: 99%
Bhargava et al.(2022) [147]	Detection d Sorting of fruits and vegetables using ML	LR, SRC, ANN, SVM	The algorithm presented attains detection accuracies of 85.49% for LR, 87.63% for SRC, 92.64% for ANN, and 97.63% for SVM for type identification. Additionally, the system achieves grading accuracies of 83.91% (LR), 85.00% (SRC), 89.54% (ANN), and 96.59% (SVM).

Author(s)	Model	Dataset	Results
Kazi et al. (2022) [148]	Fruit Classification using transfer learning	3 fruits: apple, banana, and orange	Accuracy:99%
Momeny et al.(2023)[149]	Saffron Grading using CNN	A dataset of 1869 images was created and categorized into 6 classes	Accuracy: 99.5%
Min et al.(2023)[150]	Food recognition using region enhancement network	Food2K Dataset	Food2K can serve as a large-scale, scale fine-grained visual recognition benchmark

2.5.2 Food Calorie Estimation

As living standards improve, there is a growing emphasis on effective dietary management. In today's context, technology plays a pivotal role in assisting users to monitor their food intake in a user-friendly manner, enabling more comprehensive daily dietary oversight. People are becoming increasingly conscientious about meticulously tracking their everyday eating habits. This practice aids in regulating nutritional intake, managing weight, controlling diabetes or food allergies, and cultivating healthier dietary routines to enhance overall well-being. Food calorie count stands out as a particularly pertinent indicator among the array of dietary metrics.

Numerous mobile applications have been developed to document daily meals, encompassing food names and corresponding calorie values [151], [152]. Estimating food calorie content presents a more significant challenge than food classification, as it necessitates a more comprehensive approach than just assessing texture and color. Factors such as food weight or volume, cooking methods, and ingredient composition directly impact the calorie content. Constructing a substantial dataset comprising food images, ingredient details, cooking techniques, and weights (or volumes), all annotated with calorie content, poses a considerable challenge. This constraint restricts the extensive use of DL approaches for precise calorie estimation. Although some researchers have addressed image classification aspects, their approaches only provide approximate calorie estimates for the depicted food. An overview of research endeavours within this domain can be found in Table 2.9.

Table 2.9. Summarized review in the domain of Food Calorie Estimation

Author(s)	**Model**	**Attributes and Dataset**	**Results**
Myers et al. (2015) [153]	GoogLeNet CNN model	Identification of food items, their volume, and calorie density	An application for mobile devices called Im2Calories is created to estimate food calories using images.
Ege and Yanai (2018) [151]	Multitask with 16-layer VGG network CNN	The attributes like food calories, categories, ingredients, and cooking directions are considered. Japanese and American datasets were used for training purposes.	The Multitask CNN demonstrated a related error rate of 27.4%, an absolute error of 91.2 kcal, and a correlation of 0.817.
Poply et al. (2020) [154]	CV-based model for Calorie estimation using MaskRCNN	Image database	(mAP) of about 93.7% on food item detection and an accuracy of about 95.5% on calorie estimation.
Shen et al.(2020)[155]	Food recognition and nutrition estimation using ML	Images dataset CNN	Inception-v3 and Inception-v4 perform better than others

Author(s)	Model	Attributes and Dataset	Results
Kumar et al.(2021) [156]	NN-based approach for food recognition and calorie estimation	MLP	The findings indicated that the ability to detect food items and accurately estimate their caloric levels was satisfactory.
Poply et al. (2021) [157]	Calorie estimation of food items using image segmentation and object detection	Object detection Semantic segmentation	mAP) of 89.30% for object detection and a percentage accuracy of 93.06% for calorie prediction.
Nevarekar et al(2022)[158]	Calorie estimation and other nutrients using ML	CNN	It estimates calories and nutrients in food
Razavi et al.(2023)[159]	ML approach to predict unreported micronutrients from food labels	The dataset was sourced from the Food and Nutrient Database for Dietary Studies (FNDDS).	Accuracy for B12 (0.94) and phosphorus (0.94), while the lowest are for vitamin E (0.81) and selenium (0.83)

2.5.3 Food Supply Chain

The food supply chain is a complex network involving diverse economic stakeholders, from primary producers to end consumers. It includes farmers, retailers, distributors, production facilities, and consumers [152], [160]. Regulatory entities, including government bodies, frequently encounter difficulties in obtaining reliable food-related information due to the inherent unreliability within the supply chain. This unreliability can readily give rise to issues like food fraud and compromises in food safety. Addressing this, Mao [152] introduced a credit assessment framework employing blockchain technology within the food supply chain. Their approach involved utilizing a deep learning network known as LSTM for this purpose. The evaluation process entailed the analysis of credit-related texts. Textual data containing phrases like "The fruit does not look very fresh" were categorized as "negative," while sentences expressing sentiments such as "the quality is good" were labelled as "positive." The LSTM was employed to extract features from the sentences, and these features were then used as inputs for a Deep Neural Network (DNN)-based classifier. The suggested approach demonstrated an approximate classification accuracy of 90% on a Chinese text dataset, outperforming conventional methods like SVM and NB. In their 2018 study, Mao et al. (2018) [152] effectively addressed the challenge of converting extensive credit evaluation text data into simplified assessment indicators [160].

Similarly, Kim (2014) [161] proposed a deep learning-based approach for sentence classification. This method can be evaluated using the dataset mentioned in Mao et al.(2018) [152] for comparison. These types of investigations are heavily reliant on substantial datasets, often referred to as big data. Hence, there remains a significant amount of work to be undertaken in the future, such as collecting various datasets (e.g., audio, text) specifically tailored for the food domain.

2.5.4 Quality Detection of Fruits and Vegetables

Fruits and vegetables constitute a crucial component of a nutritious diet and have garnered significant attention in research, particularly in quality assessment. Their consumption supplies vital nutrients to humans. In recent years, the amalgamation of Deep Learning, machine learning, and image processing has emerged as a potent approach for detecting fruit and vegetable quality. This synergy has proven to be highly effective. A compilation of diverse research endeavours about the assessment of fruit and vegetable quality is outlined in Table 2.10

Table 2.10. Review of the work in the area of Quality Detection of Fruits and Vegetables

Author(s)	Proposed Methodology	Techniques and Dataset	Conclusion
Li et al. (2009) [80]	The sour skin of onions was detected using SVM. PCA method was used to show the distinct clusters formed by healthy and infected onions.	SVM and PCA MANOVA for hypothesis testing.	Accuracy: 85% for validation and 81% during training. p-value < 0.0001

Author(s)	Proposed Methodology	Techniques and Dataset	Conclusion
Mustafa et al. (2011) [162]	Sorting of fruits using 17 features using morphological and colour characteristics of fruits (apple, banana, mango, orange, and carrot).	DIP, ANN, and Probabilistic Neural Network (PNN)	Accuracy: 90%.
Jhuria et al. (2013) [163]	ANN was used to detect the diseases apples (Appli Scab and Rot) and grapes (Black Rot and Powdery Mildew)	Image processing and ANN	Accuracy: 90%
Moallem et al. (2016) [164]	A computer vision-based algorithm is suggested for the grading of Delicious Golden apples, utilizing surface features	SVM, MLP, and KNN for classification and dataset included 120 images	The SVM classifier emerged as the most effective, achieving a recognition rate of 92.5% for the two categories (healthy and defective) and 89.2% for the three quality categories (first rank, second rank, and rejected ones).
Tan et al. (2016) [165]	AI-driven alert system for detecting pests and diseases in apple crops	CNN	Accuracy: 97.5%
Sahu et al. (2017) [166]	Development of an automated tool using the concept of computer vision to find the defects based on its features like shape, size, and colour.	Digital Image Analysis	The mangos were separated based on defects and maturity levels.

Author(s)	Proposed Methodology	Techniques and Dataset	Conclusion
Azizah et al. (2017) [167]	Detection of defected surfaces of mangosteen using 120 RGB images. Manual labels were acquired, resized, and cropped to dimensions of 512 × 512 pixels to create the dataset for modeling and evaluation.	CNN integrated with a fourfold cross-validation approach.	Accuracy: 97.5%
Mithun et al. (2018) [168]	Identifying artificially ripened bananas involved hyperspectral sensing and RGB imaging. 120 RGB images from each class (artificially ripened and normally ripened) were used for training, with an additional 30 images for testing to train and assess the model.	AlexNet Model	Accuracy: 90%
Sun et al. (2018) [169]	Detection of diseased peaches using hyperspectral imaging on 420 channels and 54 image features.	PCA and deep belief network	Peaches were classified well
Rodriguez et al. (2018) [170]	Discrimination of plum varieties based on their maturity level.	AlexNet Architecture	Accuracy: 91% to 97% for different datasets.
Z. Liu et al. (2018) [160]	Cucumber defect detection based on hyperspectral imaging	Stacked autoencoder in combination with CNN	Accuracy: 91.1%

Author(s)	**Proposed Methodology**	**Techniques and Dataset**	**Conclusion**
Roy et al.(2020) [171]	CV was used to detect the apple quality based on its peel.	Enhanced UNet (En-UNet)	Accuracy: 97.54%
Ren et al.(2020) [172]	ML approach for freshness prediction of fruits by measuring their moisture content	SVM, KNN, DT	Accuracy Results: 80% - 95%
Fan et al.(2020) [173]	A CNN-based architecture is developed to identify faulty apples on a fruit sorting machine operating at a detection speed of 5 fruits per second	CNN	Accuracy:96.5%, Recall: 100.0%, specificity: 92.9%,
Bazame et al.(2021) [174]	Detection and Classification of coffee fruit using darknet from video frames	YOLOv3	mAP: 84, F1-Score:82%, precision:83%, recall: 82%
Gururaj et al.(2022) [175]	Identification of mango variety based on ripening stage using CV	CNN	The accuracy achieved is 93.23% and 95.11% for variety recognition and quality grading, respectively.
Shao et al.(2022) [176]	Assessment of tomato quality using hyperspectral imaging	Multiple Linear Regression	R^2= 0.87,RMSEV = 1.33 and RPD = 2.58.
Ni et al.(2022) [177]	A method was proposed to detect carrot quality using deep CNN.	DCGAN for data augmentation Res-Net for recognition	Accurcy:98.36%
Mukhiddinov et al.(2022) [178]	Deep learning approach for fruit freshness binary classification	YOLOv4	Average Precision: 50.4%

Author(s)	Proposed Methodology	Techniques and Dataset	Conclusion
Azadnia et al.(2023) [179]	Categorize hawthorn fruit into three classes (unripe, ripe, and overripe) from image dataset	CNN	ResNet50:99.63%, Inception-V3: 100% Proposed CNN model:99.63%
Pathmanaban et al.(2023) [180]	Digital imaging to classify the quality of damaged and diseased guava fruit	CNN	Accuracy: 99.92%
Das et al.(2023) [181]	Tomato freshness quality detection using CV	ANN	Proposed ANN outperformed traditional methods
Chaturvedi et al.(2023) [182]	DL method to detect external defects in tomato	CNN VGG19, ResNet50, DenseNet201, EfficientNetB4, and Inceptionv3	Results EfficientNetB4 Accuracy: 97.97 Precision: 97% Recall: 93.00%
Knott et al.(2023) [183]	Fruit Quality Assessment using image-based ML method	Apple and Banana dataset	Accurcay:90%
Ali et al.(2023) [184]	Pineapple Quality detection using DL and thermal imaging	ResNet, VGG16, and InceptionV3	Accuracy:96.87%
Yu et al.(2023) [185]	Classification of Apples using DL-based methods	13 Classes of Apple	Accuracy: 96.1%

2.6 Findings of Systematic Survey

This section encapsulates the outcomes drawn from a comprehensive survey, which has been conducted to address all the research questions outlined in Table 2.1. The literature review highlights a prevalent utilization of machine learning and deep learning techniques, often accompanied by sensor-based approaches, as depicted in Figure 2.8. PCA has emerged as a common technique for dimensionality reduction. AI-based methods exhibit substantial potential, extending beyond labour-intensive tasks in food quality detection.

A majority of research endeavours, approximately 75%, have chosen to employ both machine learning and deep learning in tandem to identify food quality. In recent times, however, there has been a noticeable shift of interest towards learning due to its enhanced accuracy despite the additional time required for training the data. Sensor-based methodologies have also been widely explored, with a primary focus on ANN and CNN for developing systems for food quality detection. The insights regarding research question RQ3, i.e., the techniques used to detect food quality detection, are consolidated in Figure 2.8, which effectively summarizes the array of AI-based techniques employed for detecting food quality.

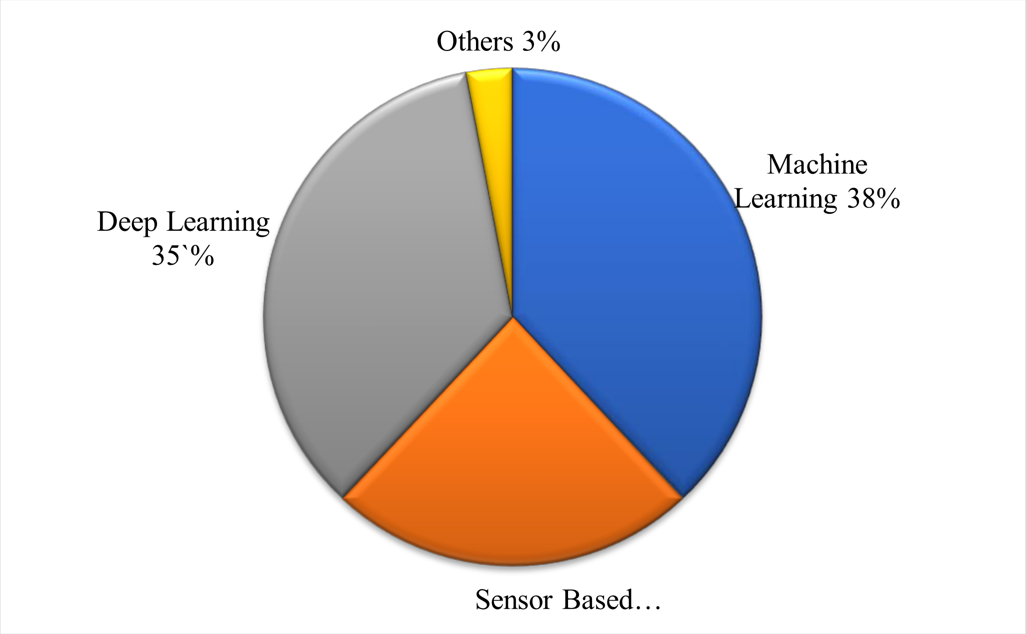


Figure 2.8. Percentage of research work for techniques used to detect food quality

Researchers have predominantly directed their attention towards certain food items, particularly dairy products like milk, cheese, and ghee. Additionally, in the realm of fruits, research investigations have encompassed a range of varieties, including apples, mangoes, oranges, bananas, grapes, and plums, among others. Quality in vegetables has been detected for various items, including carrots, tomatoes, onions, cucumbers, and spinach. Furthermore, researchers have extended their efforts to identify adulteration in diverse foodstuffs such as honey, olive oil, and saffron. The frequently contaminated food products are visually summarized in Figure 2.9.

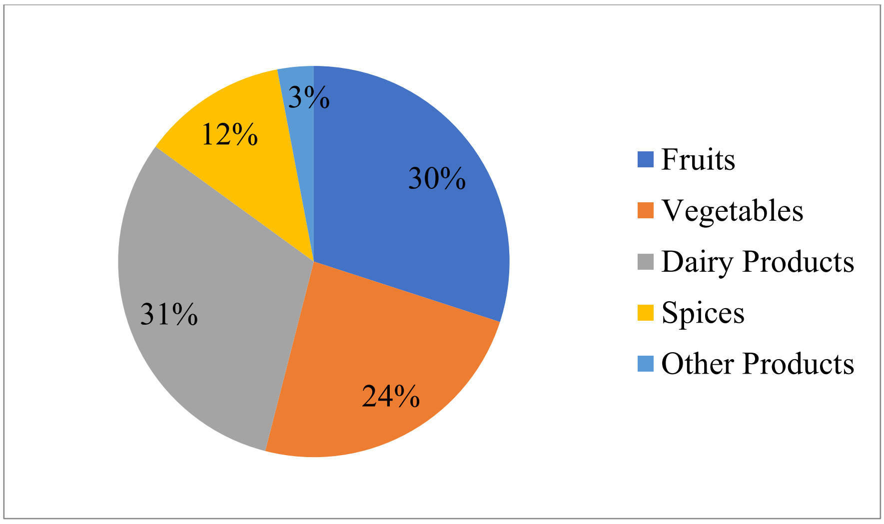


Figure 2.9. Percentage of food products that are commonly compromised due to quality

The answer to research question RQ5, i.e., "Which food items have predominantly been investigated so far for quality detection?" is concisely presented in Table 2.11, detailing the primary food items researchers have investigated to develop a food quality detection system.

Table 2.11. Commonly used food products for food quality detection

Types of Food Products	Authors
Milk/cheese/ghee	Kobek et al. (2017) [57]; Tripathy et al. (2018) [61]; Ayari et al. (2018) [117]; Lukinac et al. (2018) [186], Neto et al. (2019) [63]; Iymen et al.(2020)[91], Sowmya et al. (2021) [107], Farah et al.(2021) [92], Piras et al.(2021) [93], Lopez et al.(2022) [70], Kaushal et al.(2023) [76], Tian et al.(2023) [187], Tian et la.(2023)[125]
Cocoa Beans/Tea	Teye et al. (2013) [113], Bazame et al.(2021) [174], Kang et al.(2023)[127]
Honey	Bougrini et al. (2016) [115]; Subari et al.(2012) [112], , Phillips et al.(2022) [71], Goncalves et al.(2023) [126], Wojcik et al.(2023) [79], Medina et al.(2023)[130]

Types of Food Products	Authors
Apple	Jhuria et al. (2013) [163]; Mustafa et al. (2011) [162]; Moallem et al. (2017) [164]; Ali and Thai (2017) [188], Tan et al. (2016) [165], Kang et al. (2019) [20], Roy et al.(2020) [171], Fan et al.(2020) [173],Yu et al.(2023) [185]
Mango	Sahu et al. (2017) [166]; Mustafa et al. (2011) [162]; Nandi et al. (2016) [50]; Ali and Thai (2017) [188], Bhole et al.(2020) [143], Gururaj et al.(2022) [175]
Oranges	Mustafa et al. (2011) [162]; Li et al. (2011) [189]; Carolina et al. (2014) [51]; Rong et al. (2017) [59], Bhargava et al.(2020) [190], Mimma et al.(2022) [41], Kazi et al.(2022) [148]
Peach/Plum/Guava	Sun et al. (2018) [169], Rodriguez et al. (2018) [170], Kazi et al. (2022)[148] , Pathmanaban et al.(2023) [180]
Banana	Mustafa et al. (2011) [162]; Hu et al. (2013) [191]; Mithun et al. (2018) [168], Helwan et. al(2021) [144], Melesse et al.(2022) [146], Wu et al.(2023) [129]
Onion/ carrot	Li et al. (2009) [80], Ni et al.(2022) [177]
Tomato	Bandyopadhyaya et al. (2014) [83], Arakeria (2016) [192]; Mehra et al. (2016) [193], Shao et al.(2022) [176], Das et al.(2022) [181], Chaturvedi et al.(2023) [182]
Cucumber	Z. Liu et al. (2018) [160], Tatli et al.(2021) [122]
Rice Seeds/ Wheat Seeds	Pourreza et al. (2011) [48]; Fayyazi et al. (2017) [58]; Ali et al. (2016) [55]; Lim et al. (2017) [56]; S. Anami et al. (2018) [60], Izquierdo et al. (2019) [64], Menaka et al.(2022) [67]
Olive Oil/Sesame Oil	Rashvand et al. (2016) [86]; Ordukaya et al. (2017) [116]; Mu et al. (2015) [85], Zhao et al.(2021) [94] ;Han et al.(2022) [123], Anbalagan et al.(2022) [109], Tian et al.(2023) [125]

Types of Food Products	Authors
Chicken/Beef/Pork/Meat/Mutton	Tian et al. (2014) [7], Kamruzzaman et al. (2015) [54]; Al-Sarayreh et al. (2018) [62]; Tian et al. (2019) [118], Rady et al.(2021) [69], Geng et al.(2022) [73], Binson et al.(2023)[128]
Water/Wine/Beer	Kundu et al. (2010) [111], Debska et al. (2011) [81]; Meire et al. (2013) [82]; Yu et al. (2017) [87]
Saffron	Heidarbeigi et al. (2015) [114], Momeny et al.(2023) [149]
Turmeric/Cinnamon/Nutmeg/Chilli/ Spices	Mandal et al.(2021) [68], Jahanbakhshi et al.(2021) [65], Fatima et al.(2021) [66], Sitorus et al.(2023) [98], Sarkar et al.(2023) [97]

2.6.1 Features used for Food Quality Detection System

Extensive scrutiny of research articles has led to a comprehensive understanding, and the response to research question RQ6, i.e., “What are various factors considered for food quality evaluation?” has been documented in Table 2.12. As previously mentioned, the assessment of food items relies on visual attributes encompassing color, morphological characteristics, and texture features.

Table 2.12. Different parameters studied for food quality detection

Features	Parameters
Colour Features	RGB, HSI values, and CIE-lab colour space for maturity evaluation and colour rating
Morphological features	Shape grading and size parameters like Fourier descriptors, length, width, the difference of diameters (max, min), roundness, *etc.*
Texture features	Roughness, contrast, entropy, orientation, regularity and correlation, energy, *etc.*

a. Colour Features

Color attributes wield significant influence over consumers' decisions to accept or reject food products, as they embody indicators of freshness and quality. Images of food items are taken using the widely used RGB color model, which is based on the primary colors red (R), green (G), and blue (B). The model partitions an object into its corresponding color planes. Given that various RGB devices yield distinct RGB values for the same pixel in an image, multiple transformation techniques are employed to standardize these values. However, due to the non-linear relationship between RGB and human visual perception, the sensory characteristics of food products cannot be accurately assessed.

HSI (Hue, Saturation, Intensity) was developed to address these challenges and is a prominent method for formulating color-based image processing algorithms that align with human perception. Nevertheless, both HSI and RGB exhibit limitations in capturing subtle color variations, making them unsuitable for evaluating color changes during processing. To overcome this, the CIELAB color space was introduced, designed to encompass all colors visible to the human eye. This model is device-independent, with 'L' denoting lightness, a controlling red/green balance, and 'b' governing green/blue balance. Notably, CIELAB color space enables perceptual comparisons, wherein color differences in this space correspond to Euclidean distances perceptible to the human eye.

Researchers utilize various parameters and color space models in quality assessment for fruits and vegetables. A comprehensive overview of this analysis, including the employed parameters and color space models, is summarized in Table 2.13.

Table 2.13. Comparison of different colour features for quality analysis of fruits and vegetables

Author(s)	**Types of Fruits and Vegetables**	**Parameters**	**Colour Space**	**Accuracy**
Blasco et al. (2009b) [194]	Pomegranate	Colour Grading	Colour Grading	90.00%
Liming and Yanchao (2010) [195]	Strawberry	Grading based on external quality	CIE Lab	88.80%
Esehaghbeygi et al. (2010) [196]	Peach	Colour and Size	HIS	90%
Dorj et al. (2017) [197]	Citrus	Grading by colour	RGB	R^2=.93
Vidal et al. (2013) [198]		Colour evaluation		R^2=.92

Author(s)	**Types of Fruits and Vegetables**	**Parameters**	**Colour Space**	**Accuracy**
Prabha and Kumar (2013) [199]	Banana	Maturity evaluation	RGB	99.1%
Kalsom et al. (2014) [200]	Mango	Maturity detection	RGB	High Accuracy
Garrido-Novell et al. (2012) [201]	Apple	Maturity discrimination	RGB	95.83%
Singh et al.(2012) [202]		Colour classification	HIS	98%
Suresha et al. (2012a) [203]		Colour classification	RGB	99%
Stefany et al. (2017) [204]		Maturity detection	CIELab	98.6%
Pereira et al. (2018) [205]	Papaya	Grading by colour	RGB	94.3%
Cavallo et al.(2019)[206]	Grapes	Grading by Colour	CIELab	92%
Khojastehnazhand et al. (2019) [207]	Apricot	Color Grading	Relative R, G, B channels, gray-scale, L*, a*, and b*	Accuracy of 0.904 and 0.923 for LDA and QDA classifiers, respectively
Ramirez-Paredes and Hernandez-Belmonte (2020) [208]	Malting barley	Color	CIELab	90%
Ireri et al. (2020) [209]	Tomato	Defect discriminant by Grading	CIELab	More than 95%
Castro et al. (2019) [210]	Gooseberry	ripeness classification	Color feature extraction	Accuracy = 93.02%

Author(s)	**Types of Fruits and Vegetables**	**Parameters**	**Colour Space**	**Accuracy**
Munera et al. (2021) [211]	Loquat	Color	HSI	accuracy > 95.9%
Dhiman et al. (2022) [212]	Citrus Fruits	Color	HSV	Accuracy: 97%

b. Morphological Features

Morphological characteristics encompass shape and size and are frequently employed to classify fruits and vegetables. In the context of these food items, grading often hinges on their dimensions, with size being a determining factor. Measuring the size involves quantifying the perimeter, projected area, width, length, and minor and major axes. These attributes find widespread use in industries for automated sorting applications. The area, a scalar quantity, indicates the actual number of pixels within a region, subsequently aiding in calculating the projected area. Feature extraction leverages the pixel gap between neighboring points. Perimeter is gauged as the extent between the boundaries of the region. These attributes prove efficient post object segmentation, irrespective of the object's shape and size.

Length and width metrics are commonly utilized for measuring the dimensions of fruits and vegetables. Given that the shape of food products frequently changes during processing, it's essential to standardize the orientation for length and width measurements. The major axis corresponds to the longest line spanning an object, derived from the lengths of two boundary pixels. Perpendicular to the major axis, the minor axis is the shortest line. Shape, a vital visual attribute for describing image content, defies precise definition due to the challenge of measuring shape similarity. Shape descriptors are classified into two categories: contour-based (centered on boundary segments via local features) and region-based (centered on integral object area). Attributes such as roundness, aspect ratio, and compactness characterize the shape of food items. Within food industry quality analysis, common shape features encompass convexity, roundness, compactness, length, width, elongation, boundary encoding, length/width ratio, Fourier descriptor, and invariant moments. The diversity of morphological features harnessed by different researchers for quality analysis of fruits and vegetables is depicted in Table 2.14

Table 2.14. Comparison of different morphological features for quality analysis of fruits and vegetables.

Author(s)	Types of Fruits and Vegetables	Parameters	Morphological Features	Accuracy
Zhang et al. (2012) [213]	Apple	Shape grading	Fourier descriptors	95.24%
Ashok and Vinod (2014) [214]				88.33%
Zhang and Wu (2012) [215]	Pear	Physical properties	Depends on size	88.20%
Ohali (2011) [216]	Date	Grading by external quality	Fourier descriptors	80%
Khoje and Bodhe (2012) [217]	Mango	Physical properties	Fourier descriptors	89.83%
ElMasry et al. (2012) [218]	Potato	Sorting of irregular potatoes	Roundness, extent, and Fourier descriptors	99%

Author(s)		Parameters	Morphological Features	Accuracy
Dimatira (2016) [219]		Size-Shape	Fuzzy Logic	6 stage classification based on maturity
Zhang et al. (2014) [220], [221], [222], [223]		Irregularity evaluation	Fourier descriptors	98.10%
Xie, Wang, and Yang (2019) [224]	Carrots	Physical Parameters	shape parameters, color parameters on R, G, B, H, S and V components	96.67%
Temizkan et al. (2019) [225]	White nectarine	Color and morphological characteristics	Weight loss, pH, TSS, in-package gas concentration, decay rate, color, texture, FT-NIR	20% controlled decay rate
Raikar et al. (2020) [226]	Okra	Length of Pod	Freshness, shape, color, bruises, cuts, insects	Feature based Classification
Lin et al.(2020) [227]	Fruit dataset Citrus, mango, pumpkin, bitter gourd, tomato, towel gourd	Physical Parameters	Shape Descriptors	Precision, Recall greater than 90%

Author(s)	Types of Fruits and Vegetables	Parameters	Morphological Features	Accuracy
Han et al.(2022) [228]	Cherry	YOLOv5	Flood Filling algorithm to extract boundary details	Accuracy: 99.6%
Cong et al.(2023) [229]	Sweet Pepper	Mask RCNN	Instance Segmentation	AP: 98.1, FPS value was 5,

c. Texture Features

Texture analysis finds applicability across diverse objects, aligning with the comprehension and interpretation of human visual systems. Extracted from groups of pixels, texture reveals the distribution of elements and surface characteristics, proving invaluable in machine vision to predict surface attributes like roughness, contrast, entropy, and orientation. Texture also correlates with factors such as maturity and sugar content, offering insights into the internal quality of fruits and vegetables. Additionally, it involves extracting intensity values between pixels to discern distinct patterns within images.

Texture analysis encompasses both quantitative and qualitative approaches. Quantitative analysis entails six textural characteristics—coarseness, contrast, line-likeness, roughness, directionality, and regularity. Meanwhile, qualitative analysis identifies four features—correlation, entropy, contrast, and energy. The diverse types of texture characteristics include statistical texture, model-based texture, and transform-based texture. Statistical texture relies on an intensity value-dependent extraction matrix from pixel values and is favored for its low computational cost and high accuracy. Model-based texture incorporates fractal models, random field models, and autoregressive models. Structural texture involves lines and edges constructed through pixel intensity, while transform-based texture yields spatial domain images. A detailed overview of quality analysis for fruits and vegetables, based on varied texture features, is presented in Table 2.15.

Table 2.15. Comparison of different texture features for quality analysis of fruits and vegetables

Author(s)	Types of Fruits and Vegetables	Parameters	Accuracy
Zhang et al. (2014c) [223]	Apple	Stem end/Calyx	95.24%
Li et al. (2017) [230]		Shape, Texture	
Jana et al. (2017) [231]		Colour, Texture	
Pan et al. (2016) [232]		Texture	95.83%
Moallem et al. (2017) [164]		Statistical, texture, and geometric features	92.50%
Deepa and Geethalakshmi (2012) [233]	Mix	Shape, Texture	Texture96.00% Shape 100%
Savakar (2012) [234]		Colour, Texture	Chickoo 94.00% Apple, Lemon 93.00%
Khoje et al. (2013) [235]		Texture	Guava, Lemon 96.00%
Nozari et al. (2013) [236]	Date	Length, Width, Thickness	93.50%
Alavi (2012) [237]		Size	86.00%
Pourjafar et al. (2013) [161] [238]		Length, Width, Thickness	90%
Liming and Yanchao (2010) [195]	Strawberry	Colour, Size	Colour: 88.80%, Size: 90.00%

Author(s)	**Types of Fruits and Vegetables**	**Parameters**	**Accuracy**
Khojastehnazhand et al. (2010b) [239]	Lemon	Colour, Size	94.04%
Razak et al. (2012) [240]	Mango	Size, colour, and skin	80.00%
Sahu and Potdar (2017) [166]		Global features	The mangos were separated based on defects and maturity levels.
Naik and Patel (2017) [241]		Colour and texture	91%
Bhargava et al.(2019) [190]	Apple, Avocado, banana, orange	Colour and texture	98.48%
Ireri et al. (2019) [209]	Tomato	Calyx and stalk scar detection	Average accuracy of grading was 0.9515
Azarmdel et al. (2020) [242]	Mulberry fruit	Geometrical properties, color, and texture characteristics	Accuracy of 100%, 100%, and 99.1% and least MSE of 9.2 × 10-10, 3.0 × 10-6, and 2.9 × 10-3 for training, validation, and test sets
Khojastehnazhand and Ramezani (2020) [243]	Bulk raisin	Texture feature	Classification accuracy of modes I (6 classes of good and bad raisin) and II (15 classes) was obtained 85.55% and 69.78%, respectively

Author(s)	Types of Fruits and Vegetables	Parameters	Accuracy
Fan et al. (2020) [244]	Apples	RGB color, GLCM	Recall = 91%, specificity = 93%, accuracy = 92%
Mehendran et al.(2022) [245]	Banana	Energy, Contrast, Correlation, RMS, Homogeneity, Mean, Standard deviation, Entropy, Greenness, Kurtosis, Skewness, and Variance	Accuracy: 81.75
Li et al.(2023) [246]	Strawberry	Features based on appearance	Accuracy: 96.55%
Sinanoglou et al(2023) [247]	Banana	Texture	Banana Quality Assessment during Ripening Stages

2.6.2 Work in Progress

Ongoing worldwide research is actively exploring the realm of food quality. Addressing RQ7, i.e., "Which are the existing systems designed for assessing food quality?", below are discussions on several existing studies.

- **pH Sensing Using Electrospun Halochromic Nanofibres:** Researchers at IIT Hyderabad are developing a smartphone-based system equipped with sensors to quantify milk quality [61]. Initially, they created a mechanism to assess milk acidity via indicator paper that undergoes color changes based on adulteration levels. Additionally, they designed algorithms for mobile integration, ensuring accurate detection of color alterations.
- **Paper Strip-Based Tests:** The National Dairy Research Institute (NDRI) in Karnal has devised an inventive kit for detecting milk quality [248]. These paper strip tests swiftly identify adulterants such as neutralizers, urea, glucose, hydrogen peroxide, sucrose, and

maltodextrin. The process involves briefly immersing a strip in the milk sample, promptly revealing the strip's color change.

- **Food Sniffer:** Swiss scientists have engineered a smart portable kitchen device to assess the freshness of raw meat, poultry, or fish [249]. The wireless Food Sniffer detects the condition of these non-vegetarian products, distinguishing between freshness, spoilage, and impending spoilage. The results are relayed to a smartphone, aiding in averting food waste and ensuring food safety.
- **Paper Sensor for Milk Freshness:** IIT Guwahati researchers have pioneered a paper-based kit to gauge milk freshness and pasteurization quality [250]. Utilizing filter paper, they crafted a detector that responds to a milk enzyme, Alkaline Phosphatase (ALP). ALP's presence indicates milk quality as it reacts with the sensor to generate precipitate, highlighting microbial presence. Smartphone cameras capture color changes in the paper when dipped in milk, and the resulting RGB values are compared to thresholds to quantify ALP content and predict milk quality.
- **Fruit Sorting at Amazon:** Amazon employs machine learning algorithms to predict grocery quality, specifically fruits and vegetables, preventing wastage by ensuring consistent product quality [251]. The system assesses fruit quality through warehouse cameras and sensors, distinguishing between good and subpar items.
- **Lab on Wheels:** The Food Safety and Standards Authority of India (FSSAI) has established a mobile lab in Chandigarh to combat food quality, especially in items like milk, paneer, jaggery, turmeric, khoya, desi ghee, pulses, besan, and mustard oil [252].

The research question RQ8, i.e., “What are future research potentials from the review?” has been addressed in Section 2.5. Future work in food quality will focus on the applications of ML and DL in the food domain. The pivotal findings derived from this systematic survey in response to the research questions outlined in Table 2.1 are summarized as follows:

- Extensive research has been conducted in the field of food quality detection over a substantial period. However, this review primarily focuses on the research conducted within the past decade, providing insights into current trends in food quality evaluation.
- Annotated datasets are accessible for diverse food categories, including fruits, Italian cuisine, and Japanese dishes. Researchers can readily utilize these resources, as described and available online within this systematic review.
- Various methods for detecting food quality, encompassing machine learning, deep learning, and IoT-based detection systems, are briefly detailed in this research study.

Given the superior accuracy achieved by these techniques, researchers are particularly drawn to deep learning approaches.

- Noteworthy applications of machine learning and deep learning within the food domain are highlighted in this survey.
- This systematic review provides information about specific food items researchers have investigated to evaluate their quality.
- The survey reveals that researchers have delved into color, texture, defects, morphological features, and features aimed at extracting food product components.
- Existing ongoing research efforts are observed to be aligned with the development of a food quality detection system.

The review underscores the considerable volume of research on food quality detection across various methodologies and techniques. Consequently, these studies offer the potential for creating cost-effective and user-friendly food quality detection systems. Developing a food quality detection system tailored to the Indian market involves generating a dataset and constructing a model using available features and existing models. Furthermore, the most effective machine learning technique applied by researchers in food quality detection can be extended to an Indian context dataset.

Chapter Summary

Our impetus to undertake this systematic survey has been ignited by the proliferating research in food quality detection. While substantial research efforts have been directed towards upholding quality control in the food industry, significant challenges persist within the Indian market due to the relatively limited technical advancements in food quality detection. Developing an AI and sensor-based system for detecting food quality faces particular complexities. Although a limited number of research studies delve into comprehensive analyses of machine learning techniques for detecting food quality, our realization of the necessity for a systematic literature survey emerged after delving into pioneering research in food quality detection. As a result, this chapter is a noteworthy contribution to the literature focused on harnessing artificial intelligence for detecting food quality. Encompassing 112 research studies published within the last decade, our survey deliberately encapsulates relevant contributions. The meticulous curation of 150 research studies for inclusion in this systematic survey has been guided by a review protocol comprising research questions, information sources, as well as inclusion and exclusion criteria. The diverse outcomes of this survey have been scrutinized to glean answers to the targeted research questions articulated in this chapter.

This chapter presents a comprehensive overview of approaches to detect food quality, the principal food products under scrutiny, and crucial parameters. Through our review, a discernible pattern emerges wherein most research endeavours in this domain find expression in conference proceedings, followed by publication in journals. Further analysis reveals that machine learning (ML) and deep learning (DL) techniques (accounting for approximately 75%) substantially outweigh other sensor-based and hybrid methodologies in terms of adoption. This chapter further elucidates the diverse experimental methods researchers pursue to detect food quality and highlights distinct food categories and salient parameters warranting attention. The quest for enhanced accuracy in food quality detection systems is far from over, necessitating continued efforts. Notably, the shortage of readily accessible online datasets, owing to the lack of accompanying links provided by researchers, presents a significant hurdle. The labour-intensive process of creating annotated datasets for various food items further compounds this challenge. As we look ahead, providing these resources could greatly facilitate the endeavours of fellow researchers, streamlining their focus on refining system efficiency through innovative food quality detection techniques. The existing techniques scrutinized in this survey chart a course for future quantitative and qualitative research endeavours in this vital area.

Chapter 3

Architecture of Proposed Food Quality Detection System

3.1 Introduction of the architecture of the food quality detection system

A food quality detection system typically involves a combination of hardware and software components designed to assess and monitor the quality and safety of food products. In this thesis, the significant achievement is developing an AI-based food quality detection system. The architecture of the proposed system is presented in Figure 3.1. As the architecture shows, the model involves the quality detection of fruits and milk using the proposed algorithms.

a. Fruit Quality Evaluation

Fruit quality evaluation is a multifaceted process that involves the comprehensive assessment of various attributes and characteristics to determine the overall quality of a fruit. This evaluation is crucial in the agricultural and food industry, impacting consumer satisfaction, market value, and food safety. Modern fruit quality evaluation leverages a combination of traditional methods and advanced technologies. In traditional fruit quality evaluation, experienced individuals rely on sensory cues like color, texture, aroma, taste, and size to assess the fruit's quality. However, this approach is subjective and may lack precision. With the advent of technology, sensors and analytical instruments have been integrated into the evaluation process, providing objective and precise measurements. Advanced fruit quality evaluation utilizes a range of specialized sensors and equipment. Colorimeters measure the color intensity and uniformity, which is essential for determining ripeness and freshness. Spectrometers analyze the fruit's chemical composition, aiding in assessing sugar content and nutritional value. Texture analyzers gauge firmness, an essential indicator of fruit quality. Gas chromatographs can detect volatile compounds, assisting in aroma and flavor assessment. Data obtained from these sensors undergoes thorough analysis. Feature extraction distills essential information from the raw data, such as color features, sugar levels, texture parameters, and chemical constituents. Machine learning and deep learning models are trained on this data to develop predictive algorithms for assessing fruit quality. Based on the extracted features, these algorithms can predict ripeness, sweetness, shelf life, and overall condition. The fruit's quality is ultimately determined by comparing the obtained assessment with predefined thresholds and industry standards. This process ensures that fruits meet the desired quality criteria before reaching consumers. Real-time monitoring and assessment technologies have revolutionized fruit quality evaluation, enhancing the efficiency

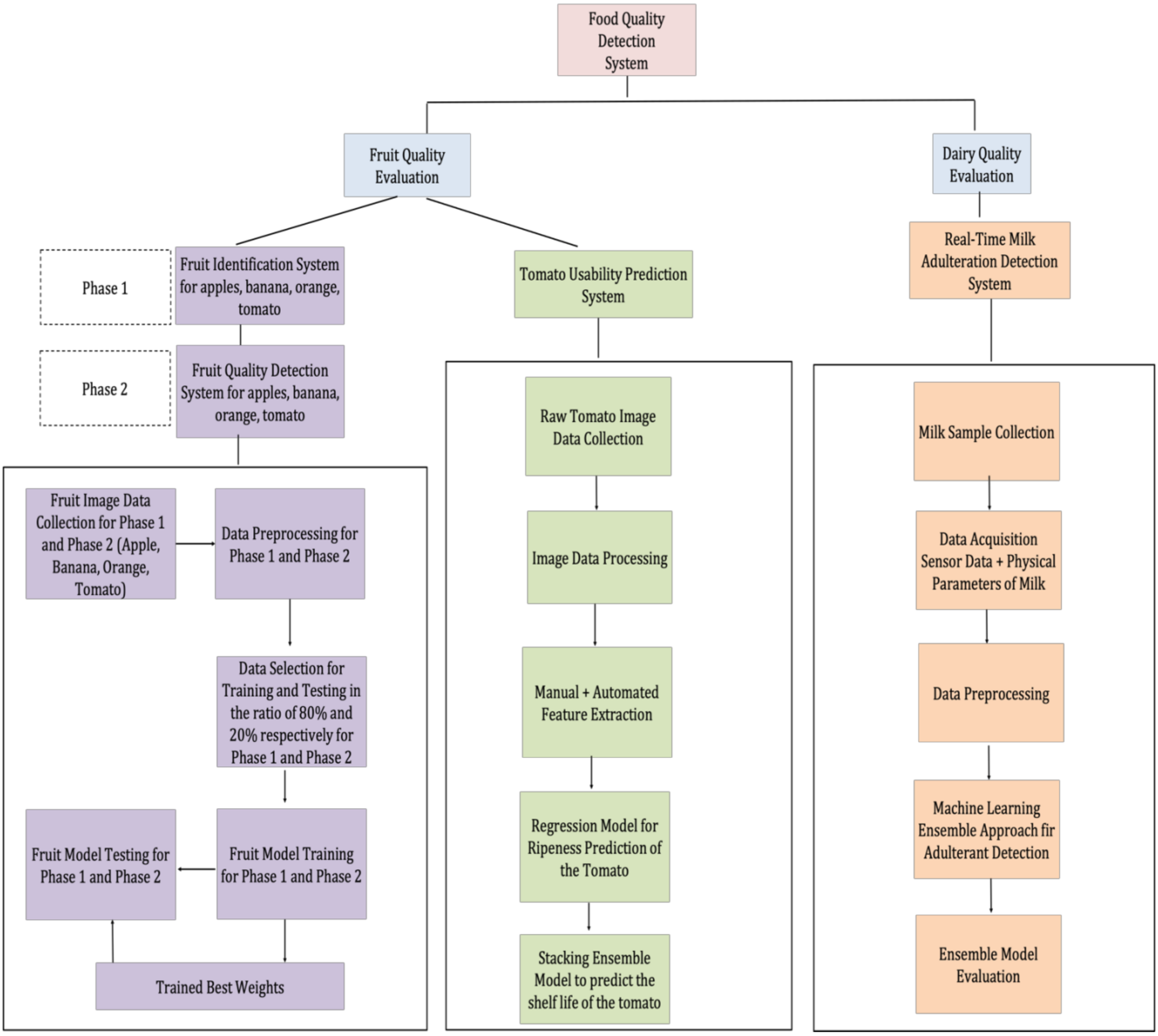


Figure 3.1 Architecture of proposed Food Quality Detection System

and fruit processing and distribution accuracy, ultimately benefiting producers and consumers.

b. Milk Quality Evaluation

Milk quality evaluation is a vital process that entails a comprehensive assessment of various attributes and components to ascertain the overall quality and safety of milk. This evaluation is critical in the dairy industry, influencing consumer satisfaction, market demand, and public health. The milk quality assessment is a multifaceted task that combines traditional methodologies with modern technological advancements. Traditionally, milk quality assessment relied on sensory evaluations performed by experienced individuals. These assessments considered parameters such as appearance, odour, taste, and texture. However, modern milk quality evaluation integrates scientific methods and specialized equipment to provide objective and accurate measurements. Advanced milk quality evaluation involves the use of specialized sensors and instruments. pH meters measure the acidity or alkalinity of milk, an essential indicator of freshness and potential spoilage. Lactometers determine the density of milk, aiding in assessing its composition, particularly fat content. Somatic cell counters are crucial in identifying the presence of abnormal cells, an indicator of milk quality and animal health. Infrared spectrometers are utilized for assessing the fat, protein, and lactose content. Data obtained from these sensors undergo preprocessing and feature extraction to extract meaningful information. Machine learning algorithms and statistical models are then employed to analyze this data and develop predictive models for measuring milk quality parameters. These assessments include determining fat content, protein levels, lactose levels, bacterial contamination, and safety. The determination of milk quality is based on comparing the assessment results with established thresholds and regulatory standards. This process ensures that the milk meets the required quality criteria before it reaches consumers. Advanced milk quality evaluation technologies have vastly improved milk processing and distribution efficiency and accuracy, enhancing food safety and consumer satisfaction in the dairy industry.

The proposed model is divided into three modules as follows.

- Fruit Identification and Quality Detection System
- Tomato Usability Prediction System
- Real-Time Milk Adulteration Detection System

3.1.1 Fruit Identification and Quality Detection System

Technological advancements in the present era have opened up new avenues for applications within the fruit industry. Automation significantly enhances economic growth and productivity within the country. Within the fruit sector, automated systems that facilitate fruit quality detection, especially amidst complex backgrounds, hold significant importance. The sorting of fruits significantly impacts the export market and quality evaluation. Notably, the appearance of fruits is a critical quality for grading, directly influencing their market value and consumer preferences. The conventional manual sorting and inspection methods are time-consuming, tedious, and exhaustive. Therefore, the need for an automated system to efficiently evaluate fruits, detect defects, and sort them based on quality is imperative.

Deep learning algorithms have significantly influenced the domain of object detection. Two prominent object detection algorithms, Mask R-CNN and YOLOv5, have been experimented with. YOLOv5 has demonstrated superior performance over the Mask R-CNN approach, especially in real-time object detection scenarios. In this study, a fruit identification and quality detection model has been developed based on the YOLOv5 object detection system. The dataset utilized for training comprises 10,545 images of four distinct fruits: apple, banana, orange, and tomato, categorized based on their quality. The model operates in two phases: firstly, identifying the fruit and subsequently detecting its quality. Mosaic augmentation has been applied to the dataset during phase 1 training, resulting in high detection performance and a robust system. The model effectively classifies the fruit, and the predicted image is then forwarded to phase 2 for the corresponding fruit quality detection. The results underscore the effectiveness of the proposed method in achieving fruit identification and quality detection on the validation dataset.

Furthermore, the real-time performance of the system has been demonstrated using sample inputs, validating the efficiency of the trained model across diverse scenarios, encompassing simple, complex, and low-quality camera inputs. Comparative analysis with several state-of-the-art detection methods confirms the promising outcomes of the fruit identification and quality detection model. The details of the working of the module have been discussed in Chapter 4.

3.1.2 Tomato Usability Prediction System

This research introduces an innovative ensemble methodology to construct a predictive system for tomato ripeness and shelf life estimation, focusing on defects and color intensity. The dataset is meticulously curated through an image acquisition system, capturing 3450 images. Various image processing techniques are employed to mitigate any aberrations in the images. To ensure the uniqueness of the ensemble approach, a range of expert-based regressors, such as SVM, DT, RF, and GBM, are utilized. Manual extraction of color, texture, and shape features yields a set of 13 features. Additionally, the Inception V3 model automatically extracts 2048 features, which are reduced to 50 through PCA dimensionality reduction. In aggregate, 63 features are leveraged for this proposed framework. The output from the ripeness regression models is categorized into three classes based on ripeness index and color intensity, determining the tomatoes' shelf life as Store, Sell, or Discount. The stacking technique is employed to make the final prediction of tomato shelf life, achieving an impressive accuracy. The study highlights that employing various features, diverse pre-processing techniques, and adept machine-learning regressors can significantly enhance the ensemble approach's accuracy compared to conventional machine-learning models. Furthermore, a comprehensive comparison of the proposed model with several state-of-the-art detection methods reveals highly promising outcomes. The details of the working of the module have been discussed in Chapter 5.

3.1.3 Real-Time Milk Adulteration Detection System

Addressing the significant concern of milk adulteration that compromises both the nutritional value of milk and consumer health, this research paper introduces a novel AI-powered Internet of Things (IoT) based multi-sensor system. Given the increasing consumption of milk as a crucial nutritional source, ensuring its safety and quality necessitates robust measures. Conventional methods for detecting adulteration have exhibited limitations, prompting the development of a sophisticated and automated approach. The proposed system integrates a diverse array of sensors capable of real-time measurements, encompassing pH, electrical conductivity (EC), temperature, gas parameters, and Volatile Organic Compounds (VOC) parameters. This comprehensive approach extends to measuring essential constituents of milk samples, such as Fat, Protein, Solids, Not Fat (SNF), Lactose, and Gravity values. To effectively identify specific adulterants, including Urea, Starch, Sodium Bicarbonate, Maltodextrin, and Formaldehyde, a machine learning-based ensemble technique is employed for classification. This ensemble approach surpasses the performance of traditional algorithms like RF, Light GBM, and Extra Trees Classifiers, achieving an impressive accuracy rate of 96% in detecting adulterants within the milk dataset. The central contribution of this study lies in creating an IoT-based data acquisition device that seamlessly integrates with the sensor system, facilitating precise and efficient measurements. Additionally, SHAP (SHapley Additive exPlanations) analysis is employed to elucidate the decision-making process of the ensemble model, enhancing result interpretability. With its real-time monitoring and accurate classification capability, the AI-powered IoT-based multi-sensor system emerges as a promising solution to combat milk adulteration. This innovation can potentially reinforce milk quality control efforts in the dairy industry. The system's swift detection and categorization of adulterants underscore its significance in addressing compromised milk quality, ensuring consumer safety, and promoting industry integrity. The details of the working of the module have been discussed in Chapter 6.

Chapter Summary

The chapter presented the architecture of a sophisticated and innovative food quality detection system designed to ensure high food safety and quality standards. The system integrates cutting-edge technologies and methodologies to evaluate and monitor the quality of food products efficiently. The critical components of the architecture have been outlined by developing the quality detection methods for fruits and milk using three modules, i.e., the fruit identification and quality detection system, tomato usability prediction system, and Milk Adulteration Detection System. Data preprocessing has been emphasized as an essential step to clean and prepare the raw data obtained from images and sensors for further analysis. Techniques like noise reduction and data normalization were highlighted. Feature extraction is another pivotal aspect discussed, encompassing the extraction of relevant attributes such as color, texture, shape, and chemical composition from the preprocessed data. These features serve as the foundation for subsequent analysis. Machine learning and deep learning models are explored as the core of the system for data analysis and prediction. These models were trained on labelled data to recognize patterns and relationships between features and food quality indicators. Quality assessment algorithms are developed based on these models to evaluate the quality of food products accurately.

Chapter 4

Fruit Identification and Quality Detection System

India, primarily recognized as an agricultural nation, boasts diverse fruits. Ranking second globally in fruit production, following China, the country grapples with substantial waste—around 40% of fruits and over 10% of total agricultural yield—attributed to inadequate transportation and distribution systems [253]. In the fruit industry, quality assessment is paramount to ensure the consumption of nutritious fruits and vegetables. In this sector, both pre-harvest and post-harvest processes are executed manually. Post-harvest fruit quality detection involves sorting, grading, and categorizing fruits as suitable for consumption or unsuitable. However, the manual sorting of fruits by proficient human evaluators is arduous, time-consuming, and prone to inconsistencies. The unreliability of this method, coupled with its variability among evaluators, underscores the need for an automated approach capable of swift defect detection and quality-based sorting. Post-harvest evaluation of fruit quality is indispensable to mitigate fruit wastage.

Fruit quality hinges on external characteristics like color, texture, shape, size, and volume, significantly influencing consumer choices. Machine vision systems have emerged as invaluable tools for ensuring quality assurance. Artificial Intelligence (AI) has ushered in a groundbreaking food science and engineering technology era. AI-based platforms, serving as alternatives for grading fruits and other perishable commodities, have introduced standardized qualitative and quantitative measures, revolutionizing the characterization of fruit profiles [254]. Notably, Machine Learning and Deep Learning, integral to AI, play pivotal roles in fruit detection and quality assessment. The need for fresh, superior-grade fruits, coupled with labour scarcity and escalating costs of skilled labour, have galvanized the development of the proposed solution aimed at enhanced efficiency and economic advantages. The automated fruit quality classifier is witnessing escalating demand and finding applications in manufacturing units, grocery outlets, and cold storage facilities [255]. The ensuing section elaborates on the contributions of this chapter.

4.1 Contribution of Fruit Identification and Quality Detection System

Researchers have conducted an analysis revealing that automated systems occasionally outperform humans in identifying fruit quality. These automated systems are poised to be pivotal in fruit-related tasks such as identification, grading, sorting, and quality assessment.

Acknowledging the necessity for advancing fruit quality detection systems, we have employed the YOLO (You Only Look Once) object detection method to precisely identify fruits and evaluate their quality. To yield effective outcomes, a novel dataset has been meticulously curated. The primary contributions of our work encompass the following:

- Development of a two-tier fruit identification and quality detection system.
- Successful application of the model to four distinct fruits, for which a real-time dataset has been meticulously generated. This dataset encompasses images captured from varying angles and diverse backgrounds, employing high- and low-resolution cameras. The images have been sourced from fruit markets, shops, roadside stalls, and similar locations.
- The development of a dataset acquisition device to collect images of fruits with different qualities based on their ripening index.
- Careful preparation of the dataset, including image enhancement through mosaic data augmentation techniques, application of diverse noise removal filters, and additional processing steps.
- Utilization of an object detection model for accurate fruit identification and quality assessment.
- Evaluation of the proposed system's efficacy by measuring the model's ability to predict testing sample labels after being trained on the extracted features from the training data.

4.2 Data Acquisition

A novel dataset has been curated to facilitate fruit quality detection. This dataset encompasses images featuring four distinct types of fruits: apple, banana, orange, and tomato [256]. These images have been captured from various viewpoints and against diverse backgrounds, employing high and low-resolution cameras. The sources of these images span fruit markets, fruit shops, roadside fruit stalls, and similar locales. This comprehensive dataset enables the AI system to assimilate zoom, contrast, and color saturation information. A subset of the images has been obtained using the acquisition box outlined in Figure 4.1. Additionally, specific images have been sourced from online repositories [19], [20], [21], [22] to augment the dataset. These images have been chosen based on their quality, aligning with vision parameters such as texture, shape, and morphological attributes. Overall, this dataset encompasses a total of 10,545 images across the four featured fruits. The images have been systematically labelled into sub-categories to enhance organization and precision, contingent on their quality and ripening stage. This categorization process has been executed in collaboration with expert fruit specialists. A breakdown of the dataset count is meticulously outlined in Table 4.1.

Table 4.1 Fruit Dataset Details Class Wise

Phase 1 Fruit Identification		Phase 2 Fruit Quality Detection	
Fruit Name	**Size of the Dataset**	**Sub Classes**	**Image Count**
Apple	2564	Apple_fresh/ripe	855
		Apple_MediumQuality	852
		Apple_rotten/defective	877
Banana	2417	Banana_Ripe	810
		Banana_Overripe	815
		Banana_Unripe	792
Orange	2413	Orange_unripe	600
		Orange_ripe/fresh	610
		Orange_mediumQuality	602
		Orange_defective/rotten	601
Tomato	3151	Tomato_defective	792
		Tomato_red	836
		Tomato_yellow	843
		Tomato_green	680

The images gathered through the utilization of the acquisition box have been captured using a smartphone camera strategically chosen to facilitate the training of a cost-effective and user-friendly AI-powered fruit quality recognition system. Capturing images through the computer vision system entails integrating three vital components: a light source, a mobile camera, and a rectangular enclosure featuring internal walls in a matte white finish aimed at mitigating reflections. LED lights with a power rating of 9W have been employed to ensure adequate lighting.

Figure 4.1. Fruit Data Acquisition Setup

The One Plus AC2001 mobile camera has been vertically positioned at the upper part, maintaining a distance of 44 cm from the sample. The box is 44 cm long, 30 cm wide, and

44 cm high. The camera lens has been set at an approximate angle of 45 degrees about the axis of the illumination source. The image capture process employed the following camera configurations: normal exposure at a shutter speed of 60 frames per second (with flash disabled), a focal length of 5mm, and an ISO value 640. A visual representation of the sample images, categorized into various fruit classes and their respective subclasses, can be observed in Figure 4.2.

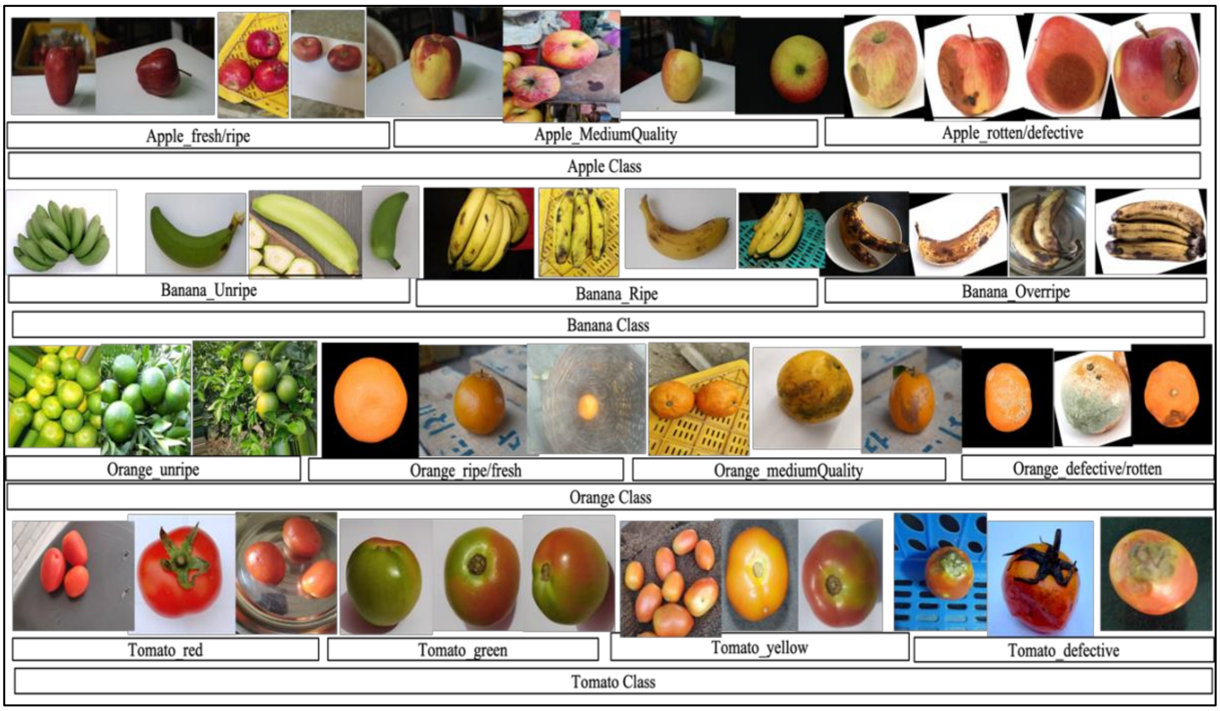


Figure 4.2. Fruit Dataset

4.3 The architecture of the proposed Fruit Identification and Quality Detection System

As outlined in section 4.2, the 10,545 collected image samples have been meticulously labelled with their respective fruit classes from the four distinct fruit categories, alongside quality labels from a pool of fourteen different options. Given the extensive number of quality labels and the model selected during the initial experimentation phase, a two-tier architecture has been proposed for the fruit identification and quality detection system.

The system focuses on fruit identification in the first phase, while the second phase is dedicated to fruit quality detection. For the phase 1 dataset, the four fruit classes—apple, banana, orange, and tomato—have been utilized. The dataset of Phase 2 has been divided into four subsets, each corresponding to a specific fruit type. These subsets are further categorized based on the ripening index, as outlined in Table 4.1.

Illustrated in the proposed architecture shown in Figure. 4.3, both phase 1 and phase 2 datasets undergo preprocessing before being inputted into the training models, adhering to a data split of 80% for training and 20% for testing. Initially, the input image undergoes phase 1 to ascertain the fruit's identity, which is then passed on to phase 2 to predict the associated fruit quality.

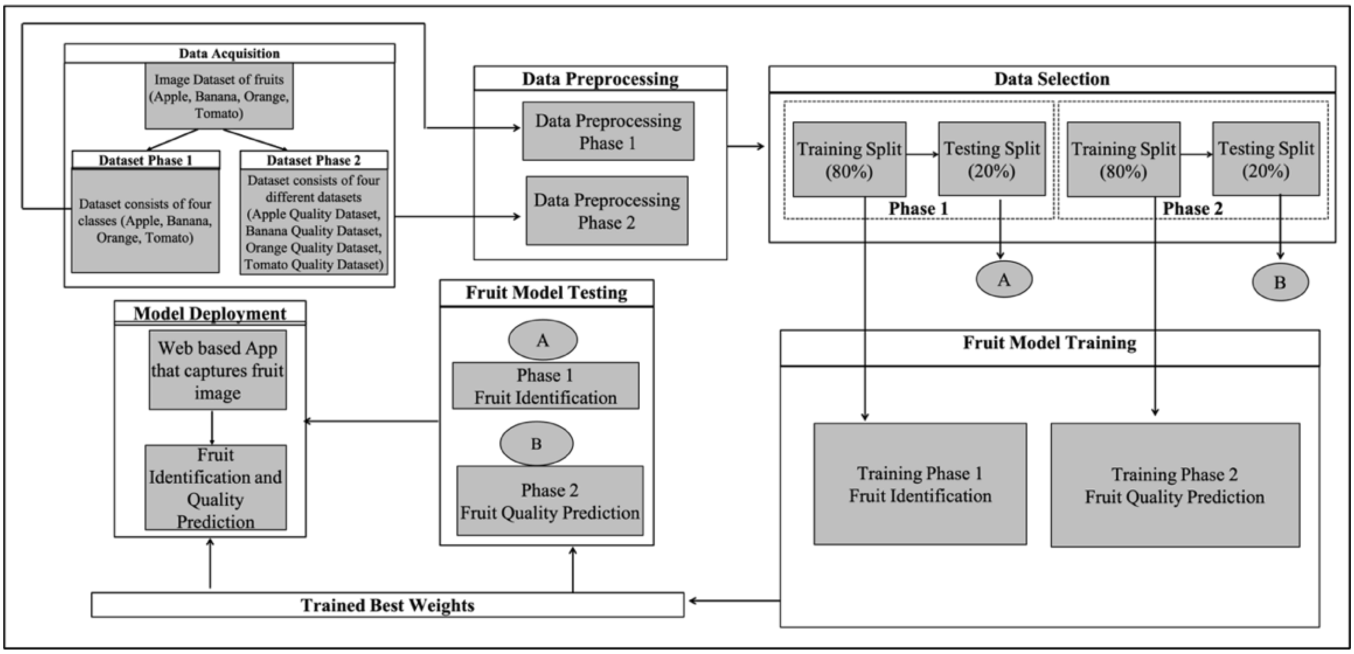


Figure 4.3. The architecture of the Proposed Fruit Identification and Quality Detection System

The section below covers the steps followed for the fruit identification and quality detection system.

4.3.1 Phase 1 Fruit Identification

The proposed model has been trained to identify the type of fruit by using the following steps.

a. Data Preprocessing of Phase 1

In phase 1, the dataset has been segregated into four distinct classes—apple, banana, orange, and tomato—as depicted in Figure 4.4. The count of images within each of these classes is detailed in Table 4.1.

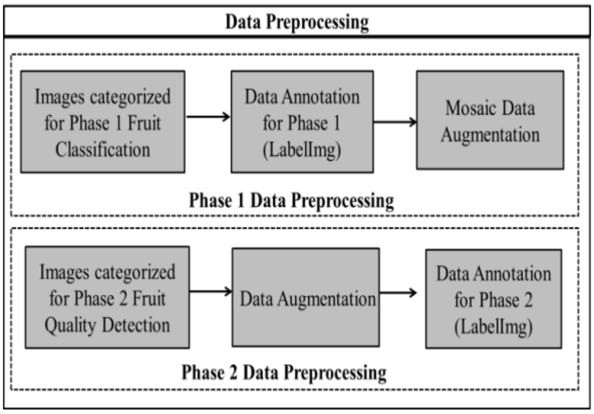


Figure 4.4. Data Preprocessing

Data Labeling

Image labeling has been executed during this phase, as illustrated in Figure 4.4. This labeling process aids in pinpointing specific objects within the images. To accomplish this, an open-source tool named LabelImg [257] has been employed for image labeling purposes. For each obtained image, bounding boxes and corresponding labels have been designated for all the fruits present in the image.

Data Augmentation

Enhancing the robustness of the fruit identification system across various scenarios requires a diverse representation of fruits. Additional insights must be garnered from the training process to mitigate the risk of overfitting the dataset. This objective has been achieved by employing a range of image transformation techniques. For the phase 1 dataset, data augmentation has been used at the pixel level, which modifies the images without altering the bounding boxes.

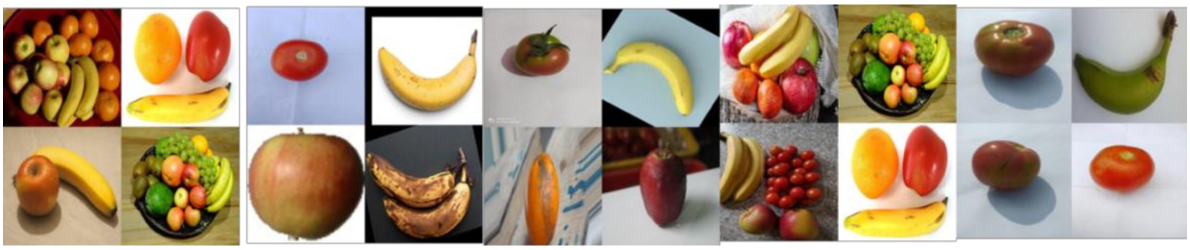


Figure 4.5. Mosaic Data Augmentation

Employing Mosaic data augmentation enhances the learning of the neural network and augments the potential for generalization within the fruit identification and quality detection model. This technique is applied to the training dataset to introduce diversity into the data. By amalgamating four distinct training images into one composite image based on scaling ratios, the model is encouraged to identify objects at reduced scales. This augmentation method is particularly advantageous in training scenarios where extensive mini-batch sizes are impractical. The mosaic-augmented dataset is visually depicted in Figure 4.5. Other image transformations have been incorporated, such as random horizontal and vertical flips and random brightness adjustments. To maintain uniformity during training phase 1, the images have been resized to dimensions of 640×640. To prevent distortion of the fruit images, padding has been introduced to preserve their original aspect ratios.

4.3.2 Phase 2 Fruit Quality Prediction

In the second phase, input from the first phase has been utilized to forecast the quality of the identified fruit. Within this stage, fruit quality is assessed by analyzing the ripening index of four types of fruits: apple, banana, orange, and tomato.

a. Data Preprocessing of Phase 2

Presented in Table 4.1, the image dataset has been subdivided into distinct categories for apples (Apple_fresh/ripe, Apple_MediumQuality, Apple_rotten/defective) and bananas (Banana_Ripe, Banana_Overripe, Banana_Unripe). Similarly, the orange dataset has been segregated into four subcategories (Orange_unripe, Orange_ripe/fresh, Orange_mediumQuality, Orange_defective/rotten). As for tomatoes, their images have been organized into four classes (Tomato_defective, Tomato_red, Tomato_yellow, Tomato_green). For each fruit type, separate quality models have been trained to predict the corresponding fruit quality. The dataset annotations align with the classes for each fruit model, a process carried out using LabelImg [257].

Data Augmentation

As depicted in Figure. 4.4 data augmentation is employed to enrich the learning process of the fruit quality detection model and enhance its overall generalization capability. This technique strengthens the resilience of the system by exposing it to diverse instances of quality fruits in various scenarios. In Phase 2, the following pixel-level data augmentation methods are employed:

- Cropping
- Padding
- Horizontal flipping
- Zooming
- Rescaling

The introduction of rotated and flipped images has enhanced the model's detection performance and robustness. Each fruit quality model's images have been resized uniformly, as outlined in Table 4.3, to ensure consistent data training. This strategy has led to improved results regarding the model's ability to accurately detect fruit quality and its capacity to handle varying situations.

4.4 Implementation of Fruit Identification and Quality Detection System

The section outlines the steps for implementing a fruit identification and quality detection system.

4.4.1 Model Selection for Proposed Fruit Model Framework

Several object detection methods, such as R-CNN, Faster R-CNN, Mask R-CNN, and YOLO, can be employed to develop a fruit identification and quality detection system. The most suitable framework for the proposed work has been determined through rigorous experimental dataset analysis.

a. Working of Region-Based Convolutional Neural Network (RCNN)

The Region-based Convolutional Neural Network (R-CNN) is an object detection framework that combines convolutional neural networks (CNNs) with region proposal methods to identify and localize objects within images accurately. R-CNN was introduced to address the limitations of earlier object detection techniques and has laid the foundation for subsequent advancements in this field. Object detection techniques such as R-CNN and Faster R-CNN utilize a Region Proposal Network (RPN) to identify regions of interest where objects might be present. The output from the RPN is then fed into a classifier that assigns classes to these regions. Another object detection approach, Mask R-CNN, introduced by He et al. [258], extends the Faster R-CNN method. It introduces an additional branch dedicated to predicting segmentation masks for objects. Mask R-CNN operates in two main stages: the RPN phase and the feature extraction phase. This method is a versatile framework for object instance segmentation and object detection. In simpler terms, Mask R-CNN can recognize various objects in an image and generate a segmentation mask for each instance of those objects. The algorithm's key strength lies in its ability to achieve pixel-to-pixel alignment, a crucial factor in Mask R-CNN's performance. In the second stage, it generates a binary mask for each Region of Interest, predicts the associated class, and calculates the box offset.

b. Working Principle of YOLO

YOLO stands as an advanced convolutional network designed for detection and localization tasks. It excels particularly in real-time object detection. The YOLO approach, depicted in Figure 4.6, seamlessly integrates object classification and detection within a regression process. This entails converting image pixels into bounding box coordinates and probabilities associated with specific classes. Unlike employing a region proposal network for predicting object boundaries and objectness scores, YOLO uses regression for precise target identification. This trade-off sacrifices some precision on one side to gain a significant speed advantage in detection on the other.

The YOLO process involves dividing the input image into an M×M grid of cells. If an object's centre falls within a particular grid cell, that cell becomes responsible for detecting the object. Consequently, bounding boxes and corresponding confidence scores for each grid cell are generated. The confidence score represents the likelihood of an object being present within the box. If the grid cell contains no object, the confidence score is set to zero. Conversely, when the object is present, the confidence score is determined by the intersection over the union between the predicted box and the actual ground truth.

Within the YOLO model, each cell is equipped with five anchor boxes. These anchor boxes incorporate a confidence score, four coordinate values (centre, width, height), and class identifiers based on standardized equations [259].

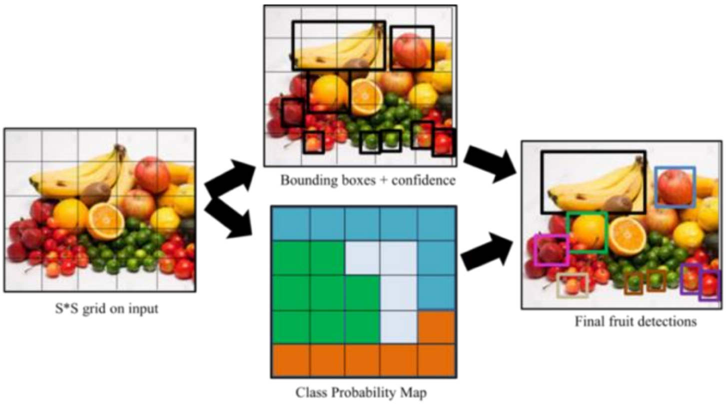


Figure 4.6. YOLO Model Detection

In contrast to other object detection systems that rely on classifiers, YOLO adopts a unique approach. It employs a single neural network to process the entire image, dividing it into distinct regions and subsequently predicting bounding boxes and probabilities for each of these regions. These projected probabilities assign weightage to the associated bounding boxes [260]. The YOLO algorithm operates through a single forward propagation within a neural network. This single deep neural network predicts both bounding boxes and probabilities by leveraging features from the entirety of the input image. This holistic training approach enables YOLO to expedite the detection process significantly [263]. YOLO encompasses various versions tailored for object detection tasks.

Among these, YOLOv5, built on the PyTorch framework, stands out due to its user-friendly nature and swift inference capabilities. As with all Single-Stage Object Detectors, YOLOv5 is characterized by three essential components: Backbone, Neck, and Head [264]. *Model Backbone*: The primary role of the model backbone lies in extracting crucial features from input images. YOLOv5 integrates the darknet with the Cross-Stage Partial Network (CSPNet) as its backbone [265]. CSPNet's core objective is to achieve gradient fusion while minimizing computational overhead. *Model Neck*: Positioned between the backbone and the head network, the model neck generates feature pyramids. These pyramids enhance model generalization across different scales, enabling the identification of objects at varying sizes. Feature Pyramid Network (FPN) [266] is employed to extract a hierarchy of in-network features. Lateral connections in the top-down path facilitate the transmission of semantically robust features, yielding strong performance. YOLOv5 uses the Path Aggregation Network (PANet) to obtain feature pyramids, enhancing information flow in instance segmentation architectures [267].

Model Head: The head is primarily dedicated to the final detection stage. Applying anchor boxes to features generates output vectors encompassing objectness scores, bounding box coordinates, and class probabilities. YOLOv5 adopts the Leaky ReLU activation function for intermediate layers, while the ultimate detection layer employs the sigmoid activation function

c. Comparative Analysis of Mask R-CNN and YOLOv5

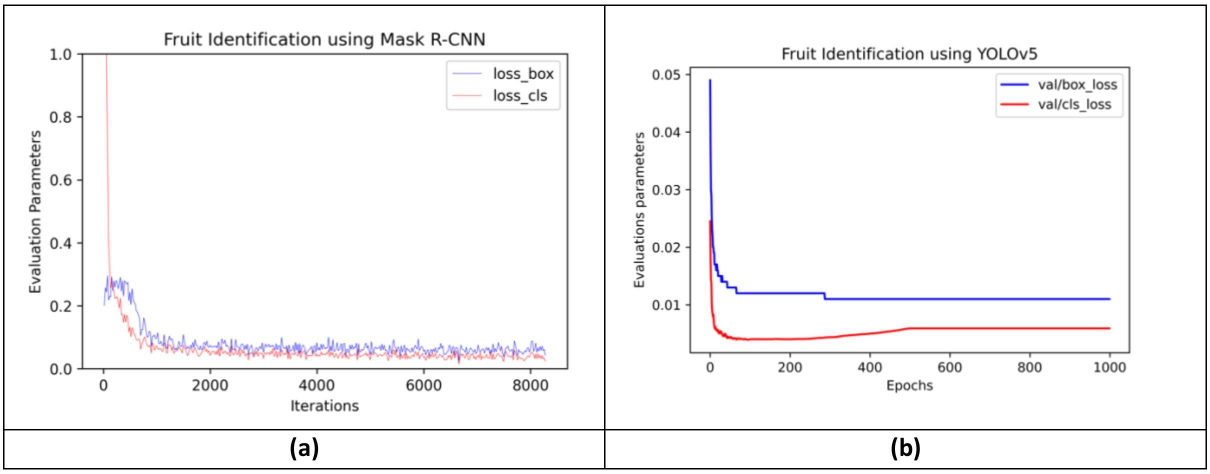
The fruit identification model was initially trained using two distinct object detection models: the Mask R-CNN model employing the Detectron2 [268] framework and YOLOv5, both utilizing the created dataset. The loss function used in Mask R-CNN is a multi-task loss that combines three components (Loss=Classification Loss+ Bounding Box Loss+ Mask Loss) whereas YOLO v5 uses a composite loss function that integrates several components to optimize detection performance (Loss= Bounding Box Loss + Objectness Loss + Classification Loss). Mask R-CNN employs IoU thresholds during both the Region Proposal Network (RPN) stage value greater than 0.7 are considered positive while value less than 0.3 are considered negative. For the final object detection phase (NMS) is applied with an IoU threshold, typically around 0.3 to 0.5. While in case of YOLO v5, it utilizes IoU thresholds during training phase at 0.5 and at inference phase NMS is applied with an IoU threshold typically around 0.4 to 0.5. The outcomes of the conducted experiments are detailed in Table 4.2. While the prediction results from Mask R-CNN are satisfactory for the task at hand, this approach involves multiple iterations on the same image, leading to a slowdown in detection speed and hindering the real-time performance of the algorithm. On the contrary the remarkable speed of YOLOv5 facilitates real-time detection, which sets it apart from other object detection models.

Table 4.2. Comparison of the proposed Phase 1 Fruit Identification model and Fruit Identification using Mask R-CNN

Fruit Model Name	**Sample Size**	**Average Recall (AR) %**	**Average Precision (AP) %**	**$F1$ $Score$ (%)**	**$Speed$**
Phase 1 Fruit Identification Model using Mask R-CNN for bounding box	Training: 8436 Testing: 2109	79.80	80.71	80.25	0.23s per image

Phase 1 Fruit Identification Model using Mask R-CNN for Segmentation	Training: 8436 Testing: 2109	87.60	82.25	84.84	32.78s per image
Phase 1 Fruit Identification Model	Training: 8436 Testing: 2109	86.80	92.20	89.42	0.10 ms preprocess, 14.10 ms inference, 1.6 ms NMS per image

Figure 4.7 graphically illustrates the evaluation parameters, including box loss and class loss, for the object detection models.



(a) (b)

Figure 4.7. Representation of parameter values of fruit identification using (a) Mask R-CNN; (b) YOLOv5

To ensure real-time applicability, the fruit identification and quality detection system should be equipped with a high-speed algorithm. The Mask R-CNN model is unsuitable for real-time applications due to its lengthy processing time. In contrast, YOLOv5 proposes an end-to-end neural network approach that simultaneously predicts bounding boxes and class probabilities. Given its speed and reliability, the YOLOv5 object detection method has been selected as the framework for developing the system to identify and assess the quality of fruits, specifically apples, bananas, oranges, and tomatoes. The subsequent section delves into the architecture of the proposed model.

4.4.2 YOLO-Based Fruit Identification Training and Testing

The preprocessed data has been partitioned into an 80:20 ratio for the training and testing subsets. The designated training data has been utilized to conduct training for phase 1. During this process, the input images have been directed through the network's backbone to extract crucial features from them, as illustrated in Figure 4.8. The neck component of the network incorporates PANet, aiding in the identification of the same fruit at different sizes and scales. Ultimately, as the images progress to the head section, final output vectors are generated. These vectors encompass bounding boxes and class probabilities, effectively characterizing the objects within the images. Based on a series of conducted experiments, the hyperparameters have been selected and initialized according to Table 4.3. These hyperparameters are employed for training the fruit dataset to achieve identification and quality detection. A grid search approach was employed to systematically explore the hyperparameter space. Cross-validation was used to evaluate the model's performance for each combination of hyperparameters. Each of them has undergone iterative training to optimize the models while varying the input resolutions (320×320, 640×640, 720×720) and batch size (8, 16, 32, 64) values. The models that demonstrated the highest accuracy under the specified hyperparameters have been chosen for further utilization. The combination yielding the highest mAP on the validation set was selected for the final model. Regular monitoring of training and validation loss was conducted to prevent overfitting, and early stopping criteria were applied if the validation loss did not improve over a certain number of epochs. The model weights have been saved in a designated directory throughout the training process. These saved weights serve as a foundation for model scalability through transfer learning in subsequent tasks related to fruit classification.

Table 4.3. Network training hyperparameter configuration for fruit model

Dataset Used	**Input Resolution**	**Batch Size**	**Learning Rate**	**Training Epochs**	**Momentum**	**Weight Decay**
Fruit Identification Model	640×640	16	0.01	1000	0.9	0.0005
Apple Quality Model	320×320	32	0.01	1000	0.9	0.0005
Banana Quality Model	720×720	8	0.01	1000	0.9	0.0005
Orange Quality Model	320×320	16	0.01	1000	0.9	0.0005
Tomato Quality Model	720×720	8	0.01	1000	0.9	0.0005

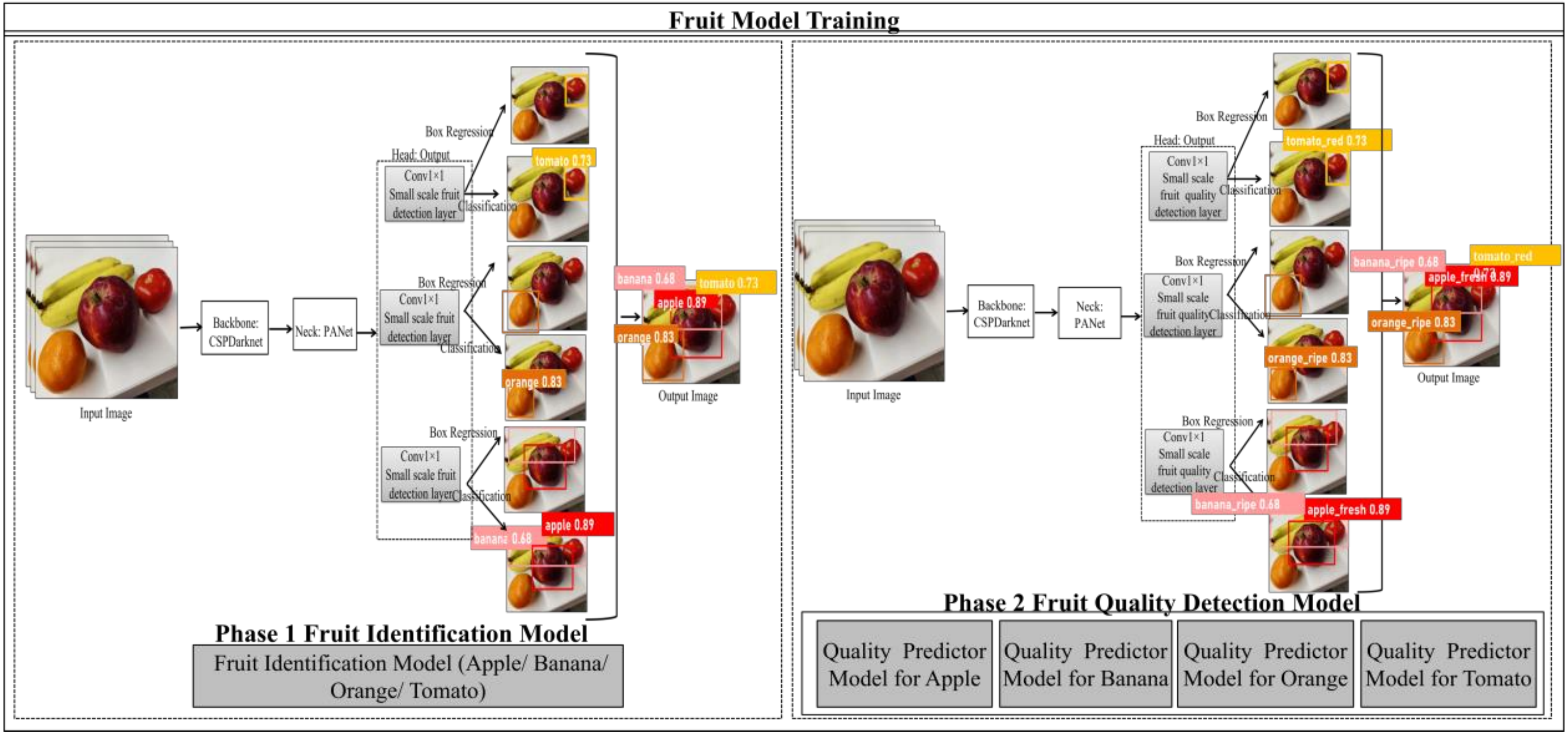


Figure 4.8. Fruit Model Training

For this study, the experiments have been conducted on a system featuring an Intel Xeon E5 2650 @2.60GHz, a 64-bit octa-core machine with 56 GB of RAM. The training process has been executed on a GPU equipped with GP102 NVIDIA-SMI Titan XP 1020 to ensure optimal performance. The choice of batch size ranged from 4 to 64, depending on the specific fruit model being utilized. The batch size is determined by the number of images per iteration, while subdivisions refer to breaking down the batch for efficient GPU memory utilization. The subdivision value is adjusted according to GPU memory constraints.

The models have been trained with images of various input sizes aligned with the specific fruit dataset. Each fruit dataset underwent training with multiple image sizes and batch sizes. However, the models chosen for further use are those that achieved the highest Mean Average Precision (mAP) values. To employ the trained weights for phase 1, the input image to be detected has been provided. This input image has been resized to match the input resolution used during training. The outcome is an image displaying identified fruits along with their corresponding labels and bounding boxes. The results from phase 1 are then passed on to phase 2 for the subsequent quality detection process.

4.4.3 YOLO-Based Fruit Quality Detection Training and Testing

As depicted in Figure. 4.4, the training dataset, which has been categorized according to the quality of each fruit, is utilized as input data for the training process in phase 2. Illustrated in Figure 4.8, the quality predictor models are trained for a predetermined number of iterations using their respective fruit quality datasets. Specific hyperparameter configurations for each quality predictor model are detailed in Table 4.3.

In the next step, the output image generated by the fruit identification model in phase 1 is passed into phase 2, along with the optimally trained weights. This setup predicts the quality of the fruits identified within the image. To achieve this, the input image is resized according to the same configuration utilized during training. The resulting output image encompasses the specified fruit quality along with predicted labels and bounding boxes. Validation of the model involves real-time tasks of fruit identification and quality detection, confirming its accuracy and effectiveness in practical scenarios.

4.5 Real-Time Fruit Identification and Quality Detection System

The evaluation of the proposed system is conducted using a validation dataset comprised of real-time images captured within bustling market environments, complete with complex and noisy backgrounds. This validation process aims to assess the performance of the system in challenging, real-world scenarios. This process is illustrated in Figure 4.9, where the input image sourced from the validation set is adjusted in size according to the dimensions specified during the training phase. The image quality is assessed by analyzing its BRISQUE (Blind/Referenceless Image Spatial Quality Evaluator) score, as outlined in [269]. This metric quantifies the quality of an image by comparing it to a baseline model derived from images of natural scenes that share similar distortions. The average BRISQUE score is computed for the training dataset, serving as the basis for establishing the model's threshold value. This crucial threshold value is detailed in Table 4.4 and plays a pivotal role in the model's decision-making process during validation.

Table 4.4. BRISQUE Score Value for Fruit Identification and Quality Detection Model

Model Name	Average BRISQUE score
Fruit Identification and Quality Detection Model	43.70

Before proceeding to phase 1 of the fruit identification and quality detection model, a series of image enhancement filters, including contrast and edge enhancement techniques, are applied if the image quality falls below the established threshold BRISQUE value. In phase 1 of the fruit identification and quality detection model, the input leveraged encompasses the complete image. However, once the model identifies the fruit, the original image is cropped in accordance with the bounding boxes derived from the fruit recognition process in phase 1 of fruit identification and quality detection model. This cropping action serves a dual purpose of reducing the overall computational load and enhancing system efficiency. The resulting cropped images, corresponding to the output labels from the fruit identification phase, are then fed into the respective quality models to predict the quality of the fruits. The amalgamation of these individual predictions yields the final comprehensive results. A significant feature of this system is its adaptability to user feedback. Feedback obtained from users regarding the recognition and quality detection outcomes of the fruit identification model is harnessed for model refinement. If users express contentment with the prediction outcomes, both the output image and its associated labels are saved for potential model retraining endeavors. This approach underscores the system's scalability through a form of transfer learning. Unlike some other studies in the domain of object detection [270], the model's initial weights can be reused as a foundation for addressing new scalability challenges, wherein user feedback plays a pivotal role in model improvement. Furthermore, the trained model can be fine-tuned by incorporating fresh images into the dataset, thus optimizing its performance and adaptability. The ensuing sections detail the outcomes of the proposed model's experimentation.

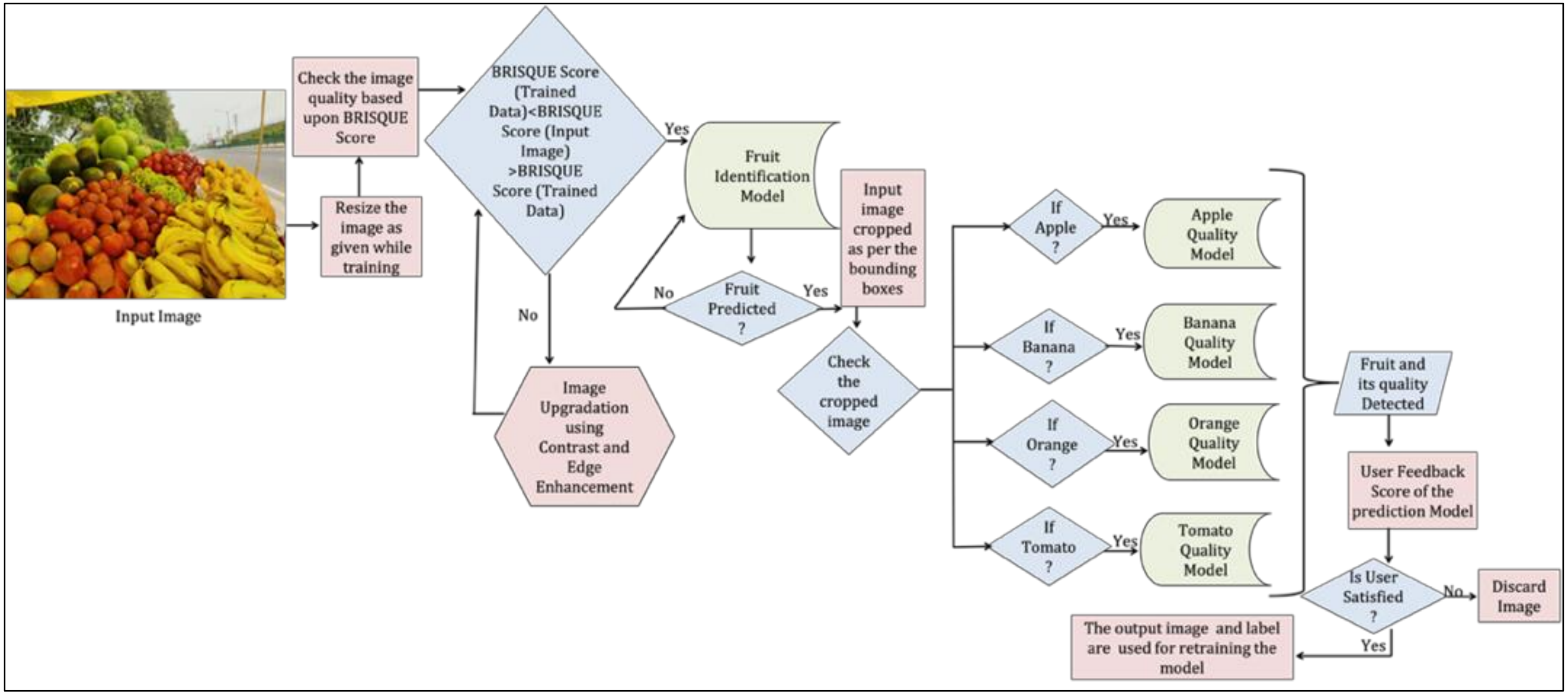


Figure 4.9. Real-Time Identification and Quality Detection System

4.6 Result Analysis of Fruit Identification and Quality Detection Model

An independent set of images, referred to as the validation dataset, comprises various fruit samples that were neither employed for training nor testing the models during phase 1 and phase 2 of the proposed system. This distinct dataset encompasses real-time images taken within bustling market settings, characterized by intricate and noisy backgrounds. The predictions are carried out on this validation dataset of images to assess the system's performance under real-world conditions.

4.6.1 Performance Metrics of Fruit Identification and Quality Detection Model

The effectiveness of the fruit model's performance has been assessed through the speed and detection accuracy metrics. The average prediction time has been employed as a key gauge of the detection speed. It's crucial for the proposed fruit identification and quality detection model to exhibit detection speed that aligns with real-time predictions for practical applicability. The subsequent performance metrics have been employed to evaluate the model's performance.

- $Mean\ Average\ Precision\ (mAP)$: This value has been calculated for each fruit model at the threshold value of 0.50 described in an equation (4.1) and to cover the whole range as discrete values for the threshold set (0.50,0.55,0.60,0.65,0.70,0.75,0.80,0.85,0.90,0.95) defined in equation (4.2).

$$mAP(0.50) = \sum_{i=1}^{4} pr(i) \tag{4.1}$$

where $pr(i)$= precision-recall area under curve value for four fruits at IoU (Intersection over Union) = 0.50 and (i) represents the fruit under consideration. IoU is defined in equation (4.3).

$$AP(0.50{:}\,0.95) = \sum_{j=0}^{9} mAP(0.50 + 0.05 \times j) \tag{4.2}$$

$$IoU = \frac{Area\ of\ overlap}{Area\ of\ Union} \tag{4.3}$$

- $Precision\ (P)$: The precision is inferred as a fraction of bounding boxes predicted that are correct as defined in equation (4.4)

$$Precision(P) = \frac{TP}{TP + FP} \tag{4.4}$$

- $Recall\ (R)$: The recall value is deduced as the fraction of all target bounding boxes correctly detected as defined in equation (4.5).

$$Recall(R) = \frac{TP}{TP + FN} \tag{4.5}$$

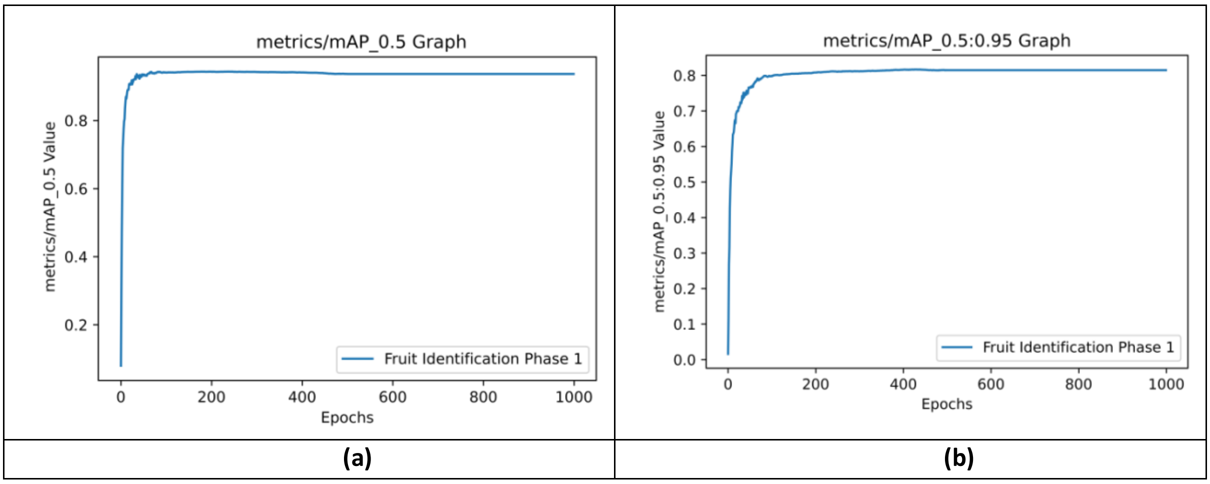
where TP: True Positive, FP: False Positive, FN: False Negative

- $F1\ Score$: The F1 Score measures the harmonic mean of the precision and recall values as defined in equation (4.6).

$$F1\ Score = \frac{2.P.R}{P + R} \tag{4.6}$$

4.6.2 Results of the Proposed Fruit Identification and Quality Detection Model

The graphs for the fruit models for $mAP(0.50)$ and $mAP(0.50{:}\,0.95)$ have been displayed in Figures 4.10 and 4.11.



(a) **(b)**

Figure 4.10. Phase 1 Fruit Identification Model graphs for (a) $mAP(0.5)$; (b) $mAP(0.5{:}\,0.95)$

In the context of the phase 1 fruit identification model, it has been observed that the mean Average Precision mAP at IoU 0.50 surpasses 90%, as depicted in Figure 4.10a, and the mAP within the range of IoU from 0.50 to 0.95 exceeds 80%, illustrated in Figure 4.10b. Shifting focus to phase 2 and the quality models, among all the fruit quality models, the Apple model exhibits the highest mAP value both for the mAP at IoU 0.50 (as shown in Figure 4.11a) and the range of mAP from 0.50 to 0.95 (illustrated in Figure 4.11b). Conversely, the banana model demonstrates the least accuracy, which could be attributed to the bounding box accommodating the banana's elongated shape. For the orange and tomato datasets, the mAP values fall between those of the other two fruit models.

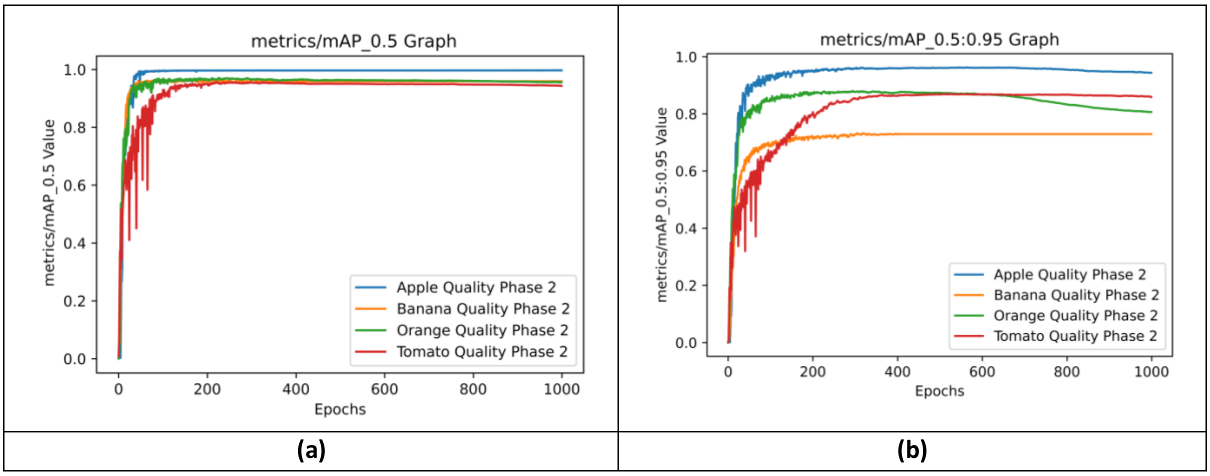
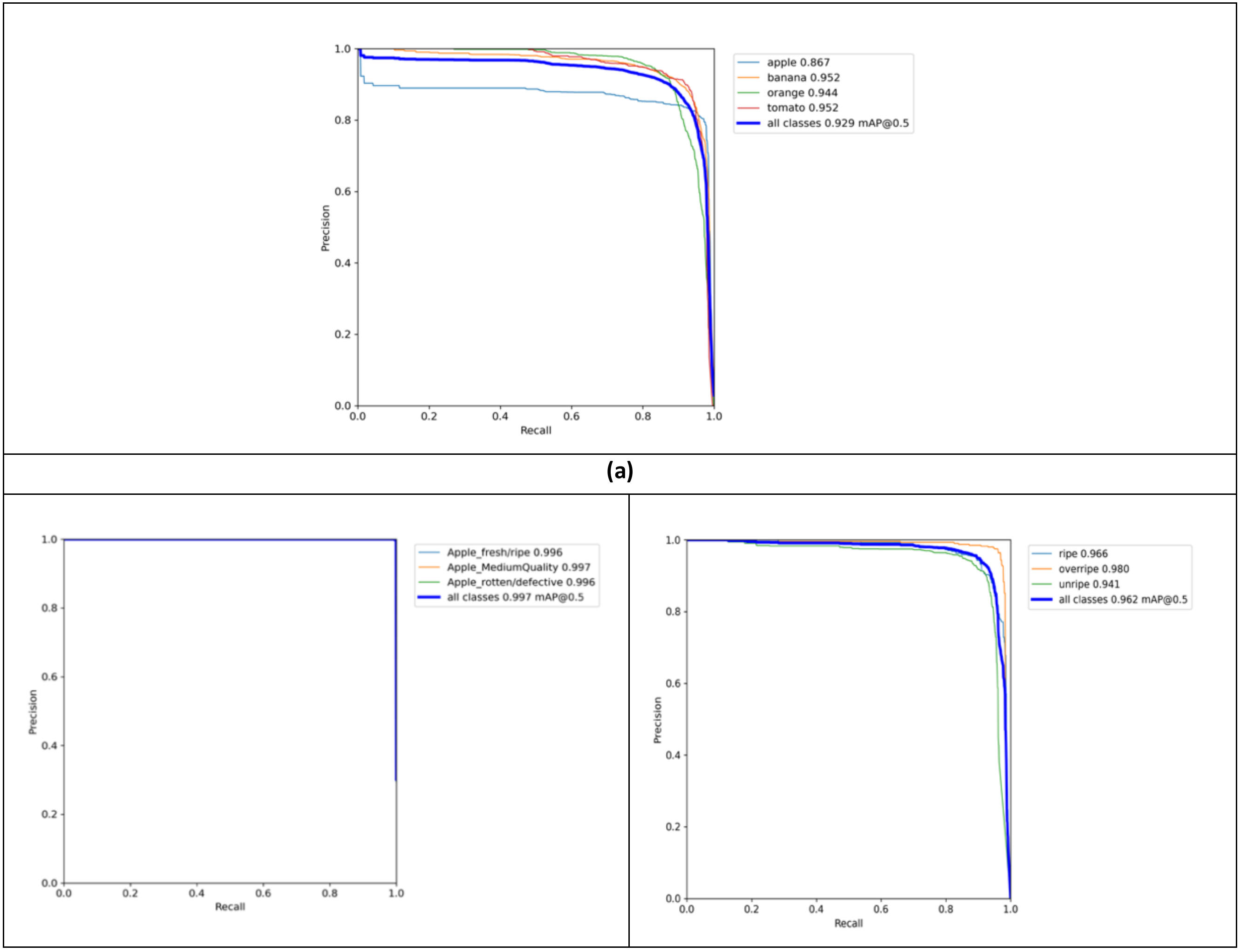
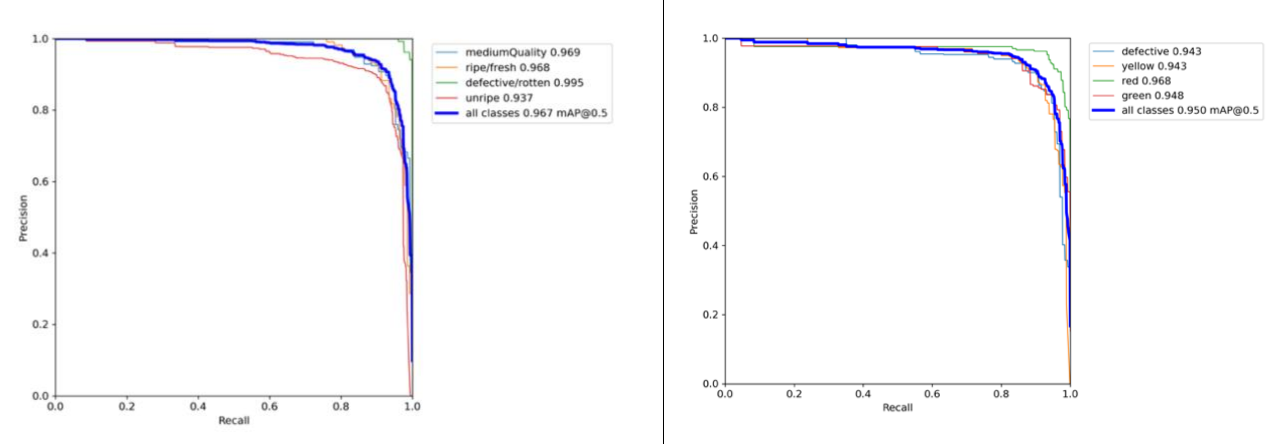


Figure 4.11. Phase 2 Quality Detection Model graphs for (a) $mAP(0.5)$; (b) $mAP(0.5:0.95)$

Visualizing the results, $Precision - Recall$ (PR) graphs for the phase 1 fruit identification model are presented in Figure 4.12a. In the case of the phase 2 quality detection model, distinct PR graphs are displayed for each fruit—apple, banana, orange, and tomato—in Figure 4.12b, 4.12c, 4.12d, and 4.12e, respectively.



(b) **(c)**



(d) **(e)**

Figure 4.12. PR Curve for (a) Phase 1 Fruit Identification Model; (b) Phase 2 Apple Quality Detection model; (c) Phase 2 Banana Quality Detection model; (d) Phase 2 Orange Quality Detection model; (e) Phase 2 Tomato Quality Detection model

Table 4.5 furnishes the mAP and various other accuracy parameters for the Phase 1 fruit identification model and each quality model.

Table 4.5. Fruit Identification and Quality Model Results

Fruit Model Name	**Sample Size**	$\boldsymbol{Precision}$ **(%)**	$\boldsymbol{Recall}$ **(%)**	$\boldsymbol{mAP}$ $\mathbf{(0.5{:}0.95)}$ **(%)**	$\boldsymbol{mAP}$ $\mathbf{(0.50)}$ **(%)**	$\boldsymbol{F1}$ $\boldsymbol{Score}$ **(%)**	$\boldsymbol{Speed}$
Phase 1 Fruit Identification Model	Training: 17960 Testing: 2496	85.60	91	92.80	90.40	88.21	0.10 ms preprocess, 3.80 ms inference, 1.9 ms NMS per image
Phase 2 Apple Quality Model	Training: 2047 Testing: 517	99.90	99.80	96.20	99.70	99.84	0.10 ms preprocess, 16.50 ms inference, 1.4ms NMS per image
Phase 2 Banana Quality Model	Training: 1930 Testing: 487	92.40	94.10	93.10	86.90	93.24	Speed: 0.20 ms preprocess, 16.80 ms inference, 3.10 ms NMS per image

Phase 2 Orange Quality Model	Training : 1925 Testing: 488	92.90	92.80	88.00	96.70	92.84	0 ms preprocess, 3.80 ms inference, 1.50 ms NMS per image
Phase 2 Tomato Quality Model	Training : 2515 Testing: 636	87.60	93.30	86.90	95	90.36	0.10 ms preprocess, 13 ms inference, 1.60 ms NMS per image

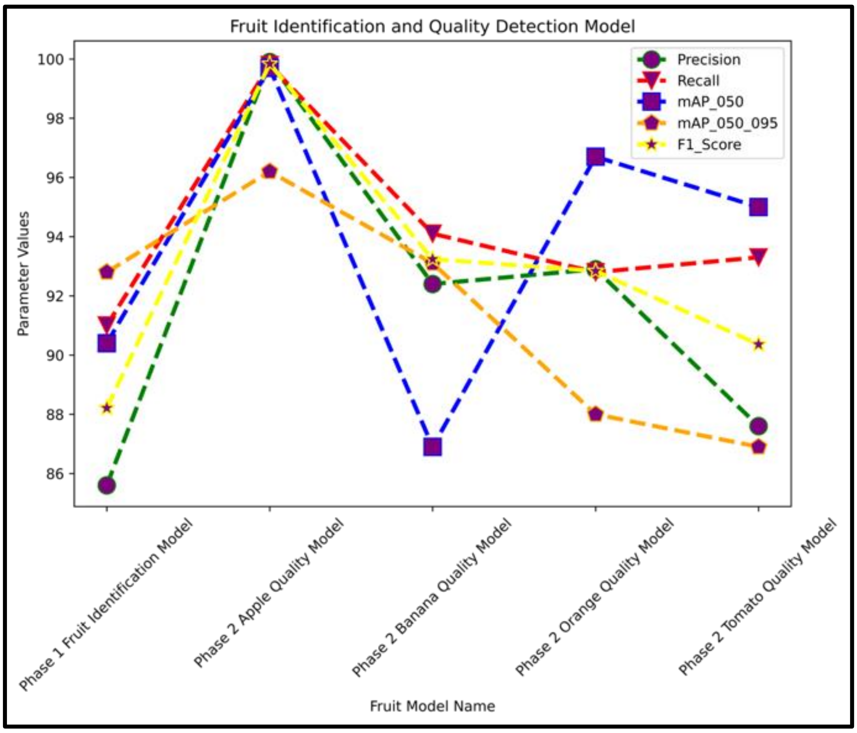
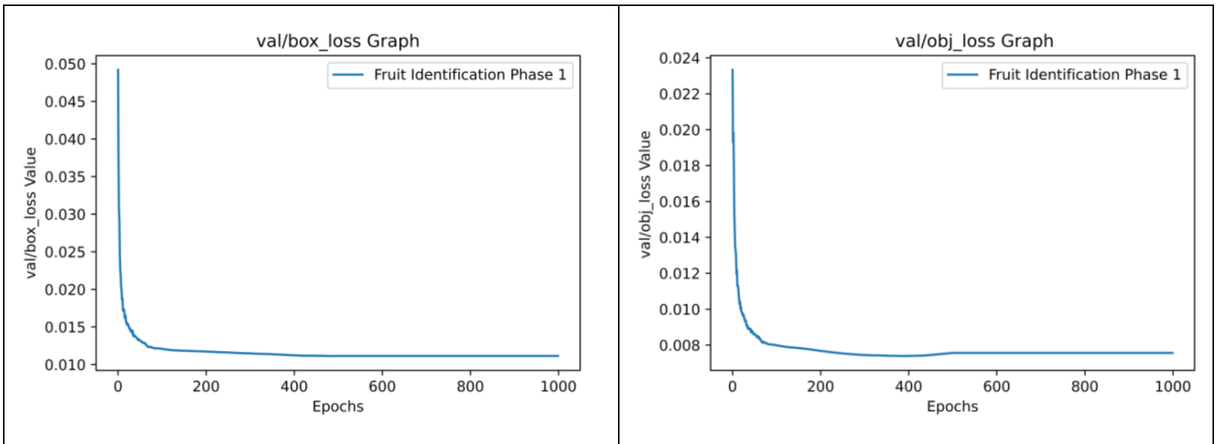


Figure 4.13. Representation of parameter values of fruit identification and quality detection model

Figure 4.13 graphically illustrates the diverse performance metrics, including Precision, Recall, mAP at IoU 0.50, mAP within the range of IoU from 0.50 to 0.95, and F1 Score, for both the phase 1 and phase 2 fruit identification and quality models. Upon simultaneous visualization of all the metrics across the models, it becomes evident that the individual quality models exhibit superior performance compared to the phase 1 fruit identification model. Moreover, the apple quality model attains the most favourable mAP outcomes. Conversely, a decline in accuracy metrics is notable for the banana and tomato quality models.

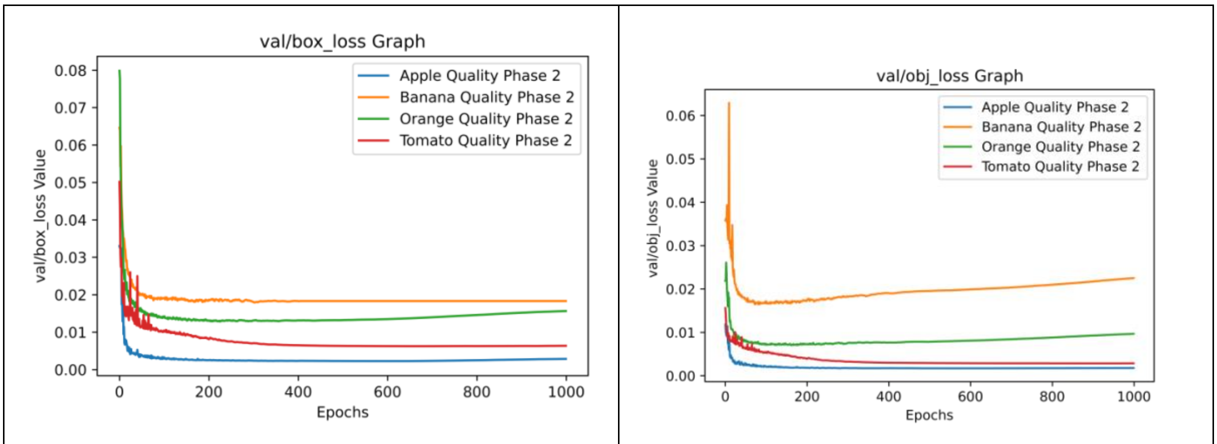
The model's prediction of the loss function is distributed into three components: one pertains to identifying bounding box coordinates, the second indicates bounding box score, and the final one predicts class score. In terms of bounding box loss, the fruit model prognosticates an objectness score for each bounding box via logistic regression. This prediction is then validated against the actual ground truth bounding box. In object prediction, the loss is determined based on whether the object is accurately enclosed by the predicted bounding box. In cases where the object perfectly fits within the predicted bounding box, the loss is calculated as 0.

Illustrations in Figure 4.14a and Figure 4.14b depict the box loss and object loss, respectively, for the phase 1 fruit identification model. The corresponding loss graphs for the phase 2 fruit quality models are presented in Figure 4.15a and Figure 4.15b, respectively.



(a) (b)

Figure 4.14. Phase 1 Fruit Identification Model graphs for (a) Box Loss; (b) Object Loss

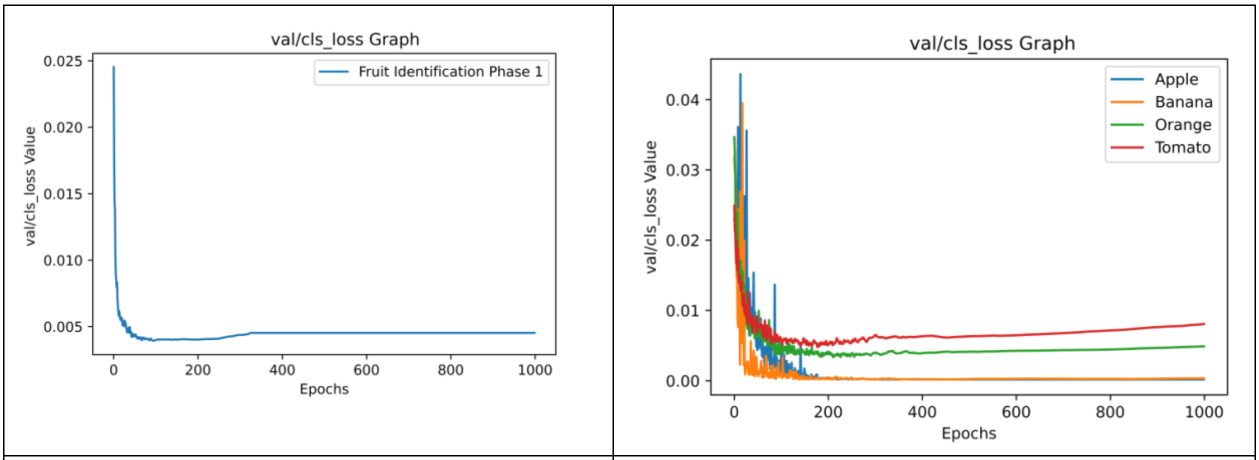


(a) (b)

Figure 4.15. Phase 2 Fruit Quality Detection Models graphs for (a) Box Loss; (b) Object Loss

In both scenarios, concerning both box loss and object loss, it's evident that the banana dataset underperforms in Phase 2, which is attributed to the notably higher loss values observed in that instance. This can be attributed to the elongated shape of bananas, causing the labelled bounding box area to be substantially more significant than the actual object to be detected. Interestingly, the loss values are below zero for the apple and tomato models. For the orange dataset, the loss value ranges between 0 and 0.01.

When considering class prediction, each bounding box forecasts the potential classes it might encapsulate through multi-label classification. The projected category for each fruit model is cross-referenced against the actual object classes. Binary cross-entropy loss is employed to address class prediction. The depiction of the class loss graph for phase 1 can be observed in Figure 4.16a.



(a) **(b)**

Figure 4.16. Class Loss graph for (a) Phase 1 Fruit Identification model; (b) Phase 2 Fruit Quality Detection Model

The class loss graph about phase 2 (depicted in Figure 4.16b) reveals that the banana and apple models yield the most favorable outcomes, as evidenced by the minimal loss values observed for these models. Conversely, the tomato dataset records the highest class loss value. This could be attributed to the similarity between the Tomato_yellow and Tomato_green categories, making their distinction challenging. Similarly to the aforementioned scenario, the class loss consistently falls within the range of 0 to 0.01 across all iterations for the orange dataset. Subsequent sections delve into the real-time validation of the system, involving the input of real-time images.

4.7 Model Testing of Fruit Identification and Quality Detection System

The proposed fruit identification and quality detection model has been applied to identify sample images. The performance of the model is evaluated using images from the test set that are not included in the training phase. These samples encompass diverse scenarios captured by users utilizing a basic mobile camera. The scenarios include complex backgrounds, images of varying camera resolutions (high and low quality), scenes from fruit stalls, roadside captures, and fruit markets. When presented with an input image, the model produces an output image containing label classes and bounding boxes, accompanied by confidence values. This output indicates the identified fruit along with its predicted quality. To thoroughly assess the model's efficacy, the validation samples are categorized into different cases:

- *Testing Case 1*: Real-time detection using images featuring simple white backgrounds, each containing a single fruit type.
- *Testing Case 2*: Images containing multiple fruits within a single frame.
- *Testing Case 3*: Images set against complex and noisy environments.
- *Testing Case 4:* Images of lower quality captured from roadways.
- *Testing Case 5:* Low-quality images taken in fruit markets and stalls.

Drawing upon the real-time fruit identification and quality detection system developed in Section 4.5, the subsequent sections present the results for each of these cases:

- *Testing Case 1*: Real-time detection with simple white backgrounds for single fruit types in each image, as depicted in Figure 4.17.

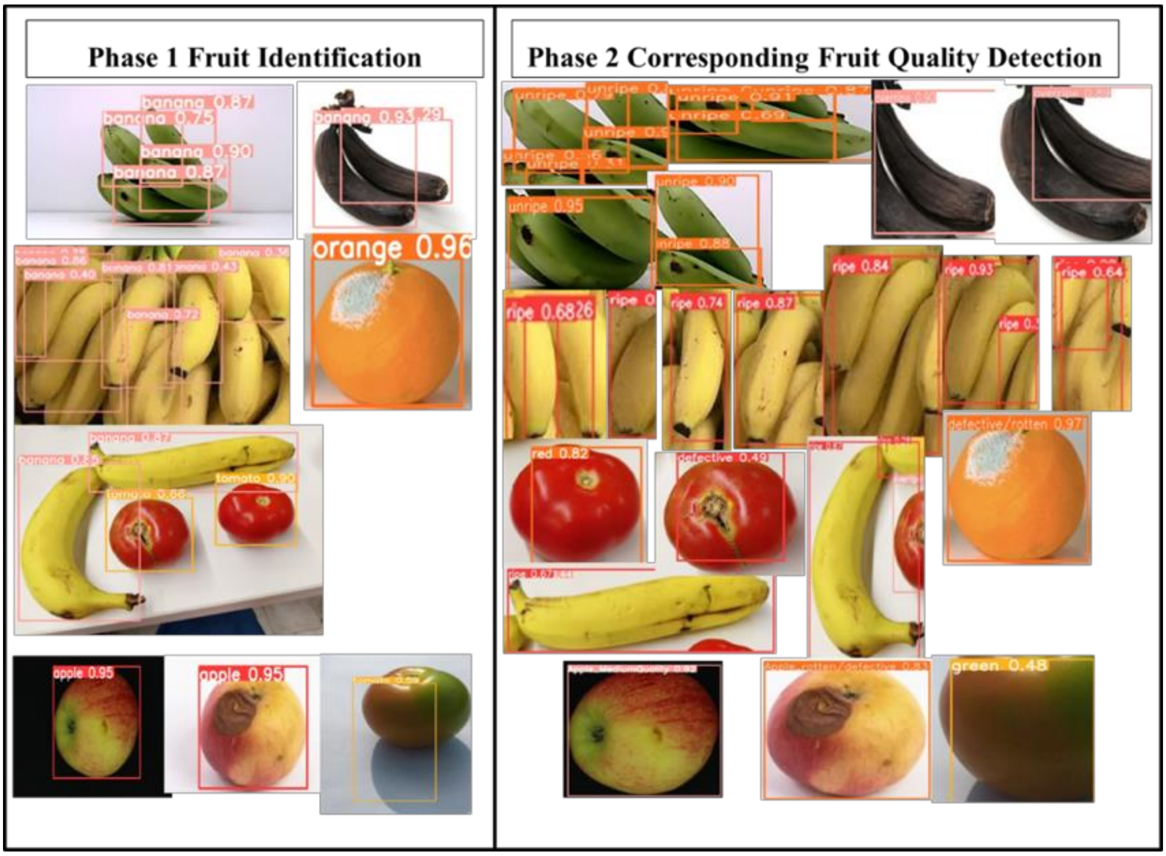


Figure 4.17. Testing Images of Fruit Identification and Quality Model with simple backgrounds and one of the fruits

For basic validation, images were taken in a controlled indoor environment. This represents the simplest form of model validation, devoid of intricate settings.

- *Testing Case 2:* Real-time detection of images containing multiple fruits within a single frame, as depicted in Figure 4.18. These images were captured using a high-resolution camera, with relatively uncomplicated backgrounds.

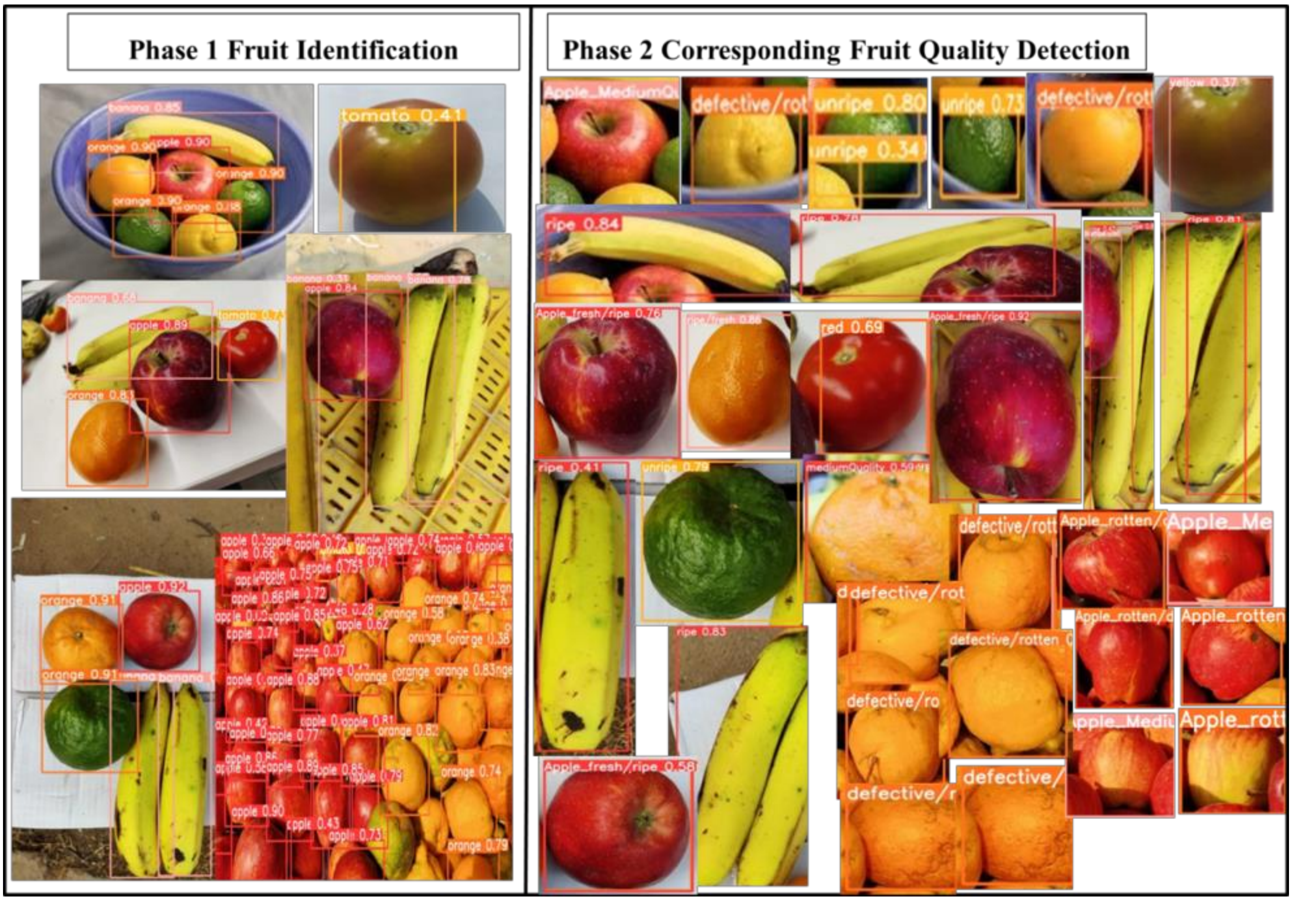


Figure 4.18. Testing Images of Fruit Identification and Quality Model with a bunch of fruits with simple backgrounds

- *Testing Case 3:* Real-time detection of images featuring multiple fruits within a single frame, set against complex and noisy backgrounds, as illustrated in Figure 4.19. These images were taken amidst fruit stalls within a bustling fruit market. High-resolution cameras were employed to capture these images.

Figure 4.19. Testing Images of Fruit Identification and Quality Model with noisy backgrounds

- *Testing Case 4:* Real-time detection of images featuring multiple fruits amidst noisy backgrounds, as presented in Figure 4.20.

Figure 4.20. Testing Images of Fruit Identification and Quality Model at fruit stalls

These images depict real-life scenarios captured at fruit stalls alongside roadways. These images were taken using a low-resolution camera to heighten the system's complexity, resulting in lower-quality pictures. When these low-quality images were input into the system, the model's performance suffered due to BRISQUE scores falling below the set threshold value. Consequently, the images underwent enhancement through contrast and edge enhancement filters, yielding the improved results showcased in Figure 4.20.

- *Testing Case 5:* Real-time detection of images depicting multiple fruits against noisy backgrounds, as depicted in Figure 4.21. These images capture real-life scenarios within a fruit market setting. A low-resolution camera was employed, resulting in images of lower quality. When these low-quality images were input into the system, the model's performance was compromised due to BRISQUE scores falling below the defined threshold. To overcome this, contrast and edge enhancement filters were applied to enhance the image quality, resulting in the improved outcomes showcased in Figure 4.21.

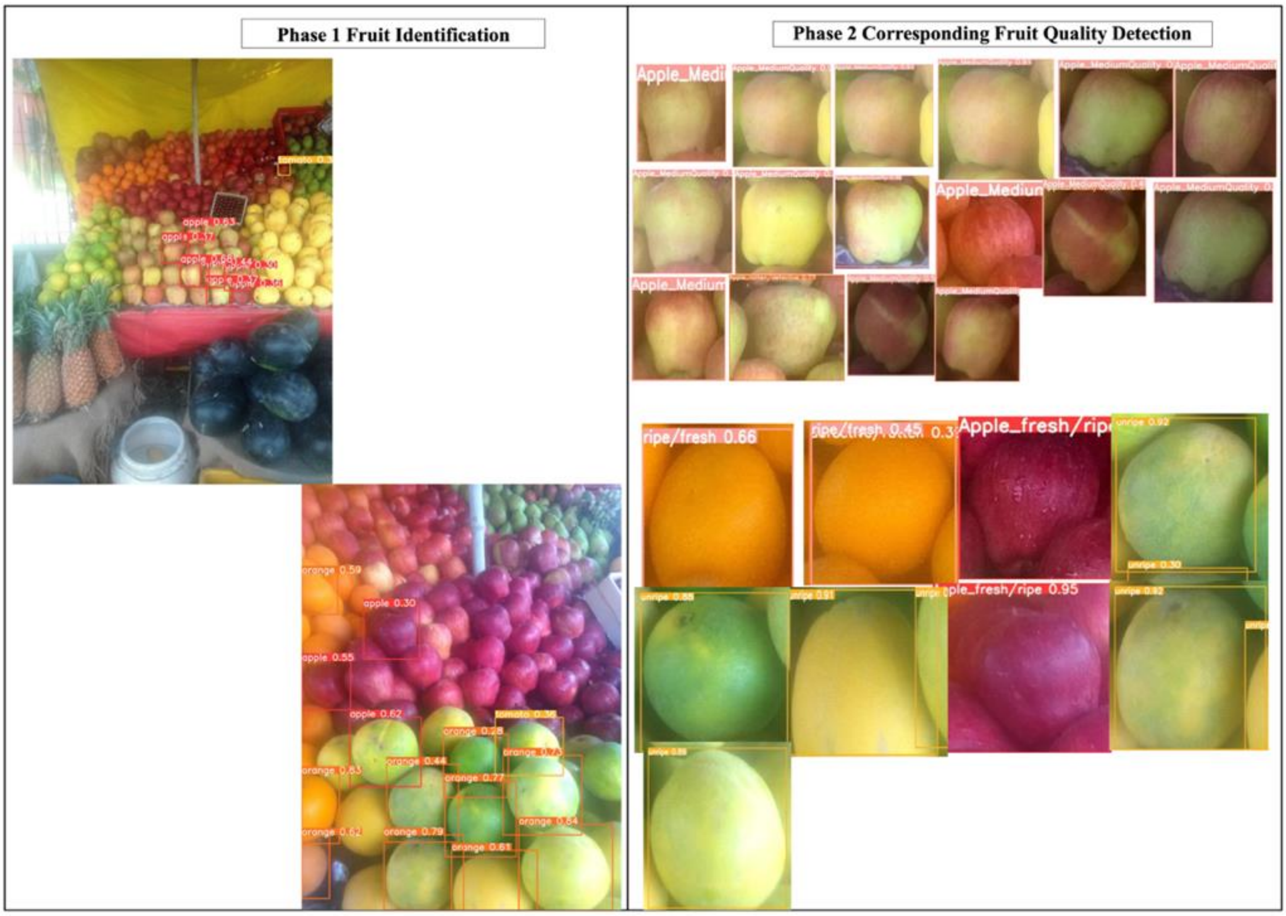


Figure 4.21. Testing Images of low-quality taken in fruit markets and stalls.

4.8 Comparison of the Fruit Identification and Quality Detection Model with State-of-the-Art

The outcomes generated by the proposed system have been compared with the findings of other existing studies centered around fruit detection and quality assessment. While most researchers have focused on single fruit detection, few have concentrated on fruit quality evaluation.

As outlined in Table 4.6, Tian et al.[22] concentrated on real-time apple detection within orchards, focusing on apple growth stages. The study involved young, expanding, and ripe apples, yielding $F1\ Scores$ of 78.30%, 79.10%, and 80.90%, respectively. In contrast, the proposed system collected three distinct types of apples based on quality (Apple_fresh/ripe, Apple_MediumQuality, Apple_rotten/defective), resulting in an overall $F1\ Score$ of 99.84% for apple quality assessment. Yan et al. [268] worked on apple detection, distinguishing between Graspable Apples and Ungraspable Apples, achieving an overall mAP of 86.75% at the speed of 0.015 s/pic. In comparison, the proposed model achieved an mAP of 99.60% with a speed of 0.10 ms for preprocessing, 16.50 ms for inference, and 1.40 ms for Non-Maximum Suppression (NMS) per image in apple quality detection. Fu et al. [269]focused on banana detection within complex orchard settings, utilizing YOLOv3 and YOLOv4 algorithms to attain 90.78% and 99.29% accuracy, respectively. In contrast, the proposed model achieved a mAP of 93.10% with a speed of 0.20 ms for preprocessing, 16.80 ms for inference, and 3.10 ms for NMS per image for banana quality detection. Chen et al.[270]employed an enhanced YOLOv4 network to detect citrus fruits in natural environments. Their citrus dataset encompassed four species (Kumquat, Nanfeng tangerine, Fertile orange, and Tangerine) captured at two stages (Growing Period and Maturity Stage), yielding 95% and 96% accuracy values, respectively with the speed .095 s/pic. In comparison, the proposed model for orange quality detection achieved an overall mAP of 96.70% across four types of oranges (Orange_unripe, Orange_ripe/fresh, Orange_mediumQuality, Orange_defective/rotten) with a speed of 0 ms for preprocessing, 3.80 ms for inference, and 1.50 ms for NMS per image. Liu et al. [271]proposed a method for Tomato detection, achieving an AP value of 96.40%. In contrast, the proposed model for tomato quality detection attained a mAP of 95% with a speed of 0.10 ms for preprocessing, 13 ms for inference, and 1.60 ms for NMS per image. The results from the proposed system are highly promising and demonstrate comparability with existing state-of-the-art techniques. For instance, Fu et al. [272]employed regression CNN and YOLO for fruit classification and fresh grading (Apple, Dragon Fruit, Kiwi, Pear, Banana, Orange), culminating in an overall mAP of 91.49. In comparison, the proposed Phase 1 fruit identification model achieved a mAP of 92.80% with a speed of 0.10 ms for preprocessing, 3.90 ms for inference, and 1.90 ms for NMS per image. As evident from Figure 4.22, the mAP values for the individual fruit quality models show improvement over existing methods, except for the tomato model.

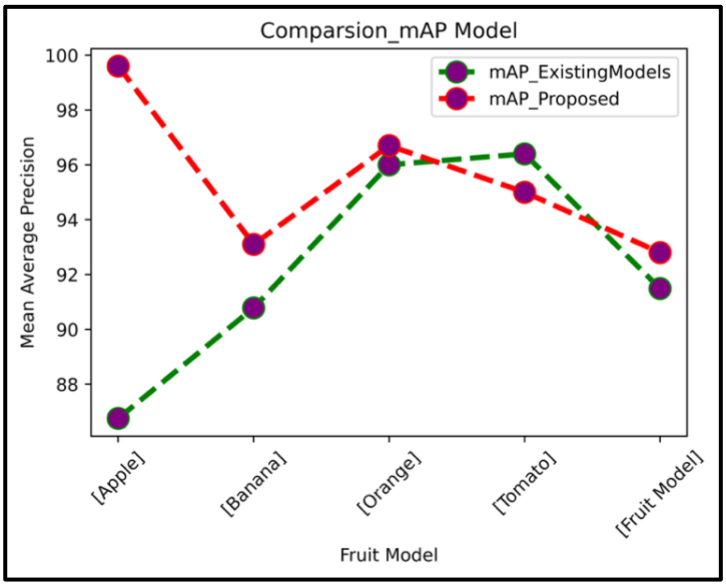


Figure 4. 22. ***mAP* Comparison of the proposed model with existing state-of-the-art-methods for Apple** [268]**, Banana** [269] **, Orange** [270]**, Tomato**[271]**, Fruit Model** [272]

Chapter Summary

A comprehensive fruit identification and quality detection model has been successfully developed, focusing on four distinct fruits: apple, banana, orange, and tomato. The model employs a two-tier framework, wherein Phase 1 handles fruit identification, followed by Phase 2 for quality prediction. The effectiveness of this approach has been demonstrated across various scenarios, encompassing simple and complex images, as well as those captured by low-quality cameras in noisy settings.

The results are highly promising, showcasing the system's prowess on the validation dataset. Phase 1 achieves an impressive mean Average Precision (mAP) score of 92.80%, while Phase 2 maintains remarkable mAP values for individual fruits: 99.60% for apple, 93.1% for banana, 96.70% for orange, and 95% for tomato quality detection models. These outcomes underscore the model's capability to identify fruits and accurately assess their quality attributes. Furthermore, the potential for expansion is evident, with the possibility of incorporating additional fruits through transfer learning in Phase 1, followed by the integration of corresponding quality detection models in Phase 2. Leveraging user feedback to refine the model adds an iterative dimension to its enhancement.

Table 4.6. Comparison of the proposed fruit model with the existing works

Fruit	**Existing Studies**						**Proposed Model**				
	Author(s)	**Number and Test Set**	**Precision (%)**	**Recall (%)**	***mAP* (%)**	**F1 Score (%)**	**Number and Test Set**	**Precision (%)**	**Recall (%)**	***mAP* (%)**	**F1 Score (%)**
Apple	Yan *et al*. [268]	2336 (Graspable and Ungraspable Apple)	83.83	91.48	86.75	87.49	Training: 2047 Testing: 517	99.90	99.80	99.60	99.84
	Kuznetsova *et al*. [273]	878	92.20	90.80	-	91.50					
	Tian *et al.* [22]	Young, Expanding, and Ripe Apples	-	-	-	78.30, 79.10, 80.90					
Banana	Fu *et al.* [269]	120 images			YOLOv4: 99.29 YOLOv3: 90.78		Training: 1930 Testing: 487	92.40	94.10	93.1	93.24
Orange	Chen *et al.*[270]	Growing Period and Maturity Stage			95, 96	91.95, 92.10	Training: 1925 Testing: 488	92.90	92.80	96.7	92.84
Tomato	Liu *et al.*[271]		94.75	93.09	96.40	93.91	Training: 2515 Testing: 636	87.60	93.30	95	90.36
Existing Model/ Proposed Model	Fu *et al*. [272]	Apple, Dragon Fruit, Kiwi, Pear, Banana, Orange	84.07	84.63	91.49	84.34	Training: 17960 Testing: 2496	85.60	91.00	92.80	88.21

Looking ahead, the model's generality can be heightened by augmenting the dataset with more fruit varieties and increasing the class diversity to bolster model quality and resilience. Modifications to the YOLO object detection algorithm could incorporate segmentation techniques to advance prediction accuracy and mitigate losses. Moreover, introducing regression capabilities to predict fruit ripeness indices could enrich the model's insights. Practical accessibility is also within reach by deploying a user-friendly mobile application, enabling end-users to identify fruits and anticipate their quality attributes effortlessly. This holistic approach marks a significant stride towards automated fruit assessment and holds promise for even broader applications in the future.

Chapter 5

Tomato Ripeness Identification and Shelf-Life Detection System

Agriculture plays an essential role and is a critical component of the overall economic development of a country. Within the realm of agriculture, fruit grading is a crucial activity because of the significant demand for superior-quality fruits in the market. The tomato stands out as a global agricultural giant among the many fruits, celebrated for its exceptional nutritional content and widespread cultivation. In botanical taxonomy, tomatoes belong to the Solanaceae family and are classified as Solanum lycopersicum. Notably, with its substantial expanse of tomato cultivation, India contributes an impressive 20 million metric tonnes of tomatoes from around 841,000 hectares of land [284]. One of the critical elements in achieving consistent tomato fruit marketing is tomato quality. The two most crucial elements that affect tomato fruit quality are ripeness and defects [285]. Assessing the ripeness stages of tomatoes is a fundamental concern within the food science and agricultural sectors, as ripeness serves as the primary determinant of tomato quality from the discerning consumer's perspective. The significance of this assessment cannot be overstated, particularly given the global importance of tomatoes as a crop. The automatic evaluation of tomato ripeness, thus, takes centre stage as a critical area of study, poised to bring significant benefits by optimizing the yield of high-quality tomato products and enhancing overall profitability. When characterizing a tomato, it is essential to consider features such as size, color, shape, texture, taste, nutritional content, defects, ripeness, etc. to define tomato quality.

Integrating an automated tomato quality grading system assumes paramount importance, conferring substantial advantages to consumers and farmers by ensuring a consistent supply of high-quality tomato produce. This chapter, therefore, advocates for the application of cutting-edge image processing techniques in designing a comprehensive system for tomato quality inspection. This approach promises to enhance the understanding of tomato characteristics related to food quality and elevate the efficiency and precision of tomato production and distribution.

5.1 Contribution

This chapter has contributed to manual and automated feature extraction of the tomato fruit for its quality evaluation regarding its ripeness and utility. The array of features such as size, color, shape, texture, and defects define the tomato quality. It proposes an ensemble machine learning model by applying regression to predict the ripeness and usability of the tomato to decide its shelf life. The image dataset used in the proposed work is manually collected by visiting various vendors in the market. The data cleaning is performed to enhance the quality by eliminating the clutter and outliers. The features selected for model training include the handcrafted and automated features using the CNN DL model. The results of the proposed system are validated by comparing them with the existing tomato quality evaluation models, and the results have proved to be encouraging.

5.2 Materials and Methods

This section discusses the data acquisition, image processing steps involved, handcrafted and automated features extracted for model preparation, and machine learning algorithms used for the proposed model for predicting the ripeness and usability of tomatoes.

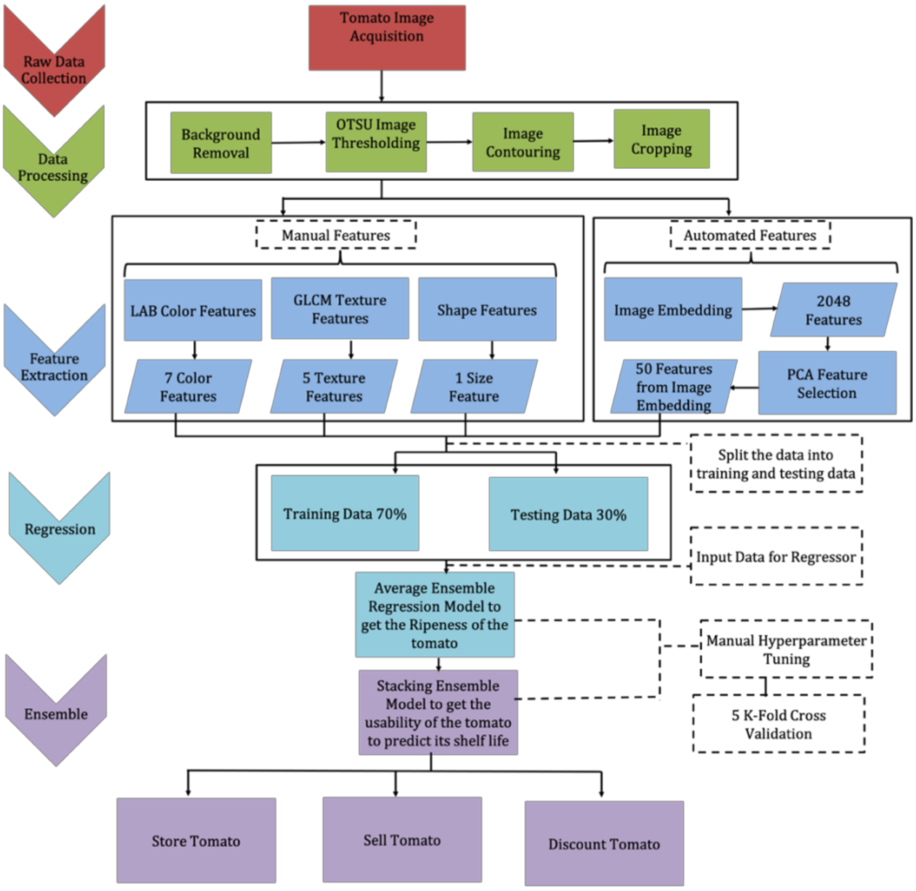


Figure 5.1. Architecture of the Proposed Model for Tomato Ripeness and Shelf Life Prediction

The overall working architecture of the proposed framework is represented in Figure. 5.1. A series of image processing steps is employed to eliminate the outliers in the acquired tomato images. The feature extraction process encompasses manual color, texture, and shape extraction, yielding 13 features. In parallel, the Inception V3 model extracts 2048 automated features, which are reduced to 50 by applying the PCA dimensionality reduction method. In aggregate, 63 features are harnessed for the proposed study. A range of expert base regressors, including SVM, DT, RF, and GBM, are employed to ensure distinctiveness within the ensemble component of the proposed technique. The outcomes produced by the ripeness regression models are categorized into three classes based on ripeness index and color-magnitude. These categories, namely Store, Sell, and Discount, provide insight into the shelf life of the tomatoes. The stacking method is employed to culminate in the final prediction of tomato shelf life, allowing for an informed and accurate estimation. The components of the architecture are discussed in the following sub-sections.

5.2.1 Experimental Setup and Data Collection

3380 images with varying degrees of defects and red color intensity are chosen from the local market vendors. The images are captured using an image acquisition system with a smartphone camera, as discussed in Section 4.2 of Chapter 4. The sample images used in the dataset are presented in Figure 5.2. The ripeness values are assigned from 0 to 8 to each of the images with the help of professional experts in fruit grading, as per Table 5.1.

Table 5.1. Pseudo Code for assigning Ripeness Values to the Tomato Images

```
Input image, image_colour, touch, texture, taste, colour_patches:
          IF(image_colour = “green” AND
             touch = “very hard” AND
             texture = “grainy” AND
             taste = “tart”) THEN
                IF(colour_patches = “unripe green”)THEN
                  ripeness =0
                ELSE IF(colour_patches = “slightly green”) THEN
                  ripeness =1
                ELSE IF(colour_patches = “yellowish green”) THEN
                  ripeness =2
                END IF
          ELSE IF(image_colour = “yellow” AND
                  touch = “less hard” AND
                  texture = “smooth and less grainy” AND
                  taste = “tangy”) THEN
```

```
      IF(colour_patches = “pale yellow”)THEN
        ripeness =3
      ELSE IF(colour_patches = “fully yellow”) THEN
        ripeness =4
      END IF
ELSE IF(image_colour = “red” AND
        touch = “moderately firm” AND
        texture = “smooth and juicy” AND
        taste = “sweet”) THEN
      IF(colour_patches = “slightly red”)THEN
        ripeness =5
      ELSE IF(colour_patches = “fully red”) THEN
        ripeness =6
      END IF
ELSE IF(image_colour = “discoloured red” AND
        touch = “soft and mushy” AND
        texture = “deteriorated and slimy” AND
        taste = “bitter”) THEN
      IF(colour_patches = “brownish red”)THEN
        ripeness =7
      ELSE IF(colour_patches = “red with black spots”) THEN
        ripeness =8
      END IF
END IF
```

Figure 5.2. Sample Dataset of Tomatoes

The proposed model aimed to develop a tomato ripeness and utility prediction system based on defects and color intensity. The image processing steps are performed to handle noisy and distorted images. Feature extraction is then performed on the entire image set to acquire manually crafted and valuable automated features [287] such as color values, shape, size, texture, etc. The extracted features, combined with embedded features, are fed as input to the ensemble model to predict the ripeness and utility of the tomato fruit to get the shelf life of the tomatoes. The steps are discussed in detail in the following sections.

- **Characterization of Tomato for dataset preparation**

Tomato characterization refers to the process of describing, categorizing, and analyzing the attributes, qualities, and properties of tomatoes. This can encompass many factors, including their appearance, taste, texture, nutritional content, and even genetic characteristics. By characterizing tomatoes, researchers, farmers, and food scientists can better understand and work with this versatile fruit, whether for agricultural purposes, culinary applications, or scientific research.

A green, unripe tomato signifies that the tomato is at an early stage of development and is not yet fully mature. Regarding their characterization, green tomatoes are usually firm to the touch, indicating a lack of softness and juiciness. These unripe tomatoes tend to be more tart or sour in flavour compared to their sweet, ripe counterparts. The absence of sugars and higher levels of organic acids contribute to this taste profile. Also, the texture of an unripe tomato is often less juicy and can be somewhat grainy or mealy, as the fruit's cells have not fully developed and softened. It's important to note that while green, unripe tomatoes may not be suitable for immediate consumption.

The coloration of the yellow tomato is an indicator of its moderate ripeness, as it has transitioned from green to a more mature state, but it has not reached the entirely red stage. They are typically firm but not as hard as green ones. They exhibit a gentle yield when gently pressed, which signifies a certain level of ripening. The flavour of a moderately ripe yellow tomato is likely to be a balance between the tartness of an unripe tomato and the sweetness of a fully ripe red tomato. It may have a milder, slightly sweet, and tangy taste. Yellow tomatoes have a smoother and less grainy texture than unripe green tomatoes. The nutritional content of a yellow tomato may be more balanced than an unripe tomato, with a greater concentration of certain nutrients like carotenoids that contribute to the yellow color.

When perfectly ripe, a red tomato is characterized by several distinct attributes that make it an ideal choice for consumption. It exhibits a deep, vibrant red color throughout its surface. A ripe red tomato should yield slightly to gentle pressure when touched. It is neither too hard nor overly soft, striking the right balance that makes eating enjoyable. It is sweet, juicy, and full of the characteristic tomato taste. Ripe red tomatoes are often described as having a well-balanced combination of sweetness and acidity. They have a smooth, juicy, and tender texture. Ripe red tomatoes are rich in essential nutrients, particularly lycopene, known for its antioxidant properties. They also provide vitamins, minerals, and dietary fiber.

A rotten tomato, also known as an overripe or spoiled tomato, can be identified by various characteristics that indicate its deterioration and unsuitability for consumption. They often exhibit a darker and discoloured appearance. They may turn brown, black, or mouldy depending on the deterioration stage. Rotten tomatoes are usually very soft and mushy to the touch. They lack the firmness that is typical of ripe or moderately ripe tomatoes. A strong, unpleasant, and often foul odour is a prominent characteristic of rotten tomatoes. They may taste sour or bitter or have an off-putting, mouldy flavour. The texture of a rotten tomato is deteriorated, with the flesh often being slimy or mushy. Mould growth, discoloration, and visible signs of decay are common indicators of a rotten tomato.

Tomatoes come in various shapes, sizes, colours, and flavours, making their characterization a rich and multidimensional field of study. These tomato characteristics lead to extracting manual features required for tomato quality prediction, as discussed in Section 5.2.3.

5.2.2 Image Preprocessing

The issues arising from image noise, suboptimal image quality, background interferences, shadow presence, and diverse textural characteristics within the image are effectively addressed using image processing techniques, as illustrated in Figure 5.1. The intricate process of preprocessing, which encompasses these essential steps, is thoroughly expounded upon in the subsequent sections.

a. Background Removal

In the current study, image segmentation eliminates the background from the tomato images. This technique divides the image into distinct segments, assigning a label to each pixel. This task is effectively achieved using the U-Net (U-shaped encoder-decoder network) CNN model, which operates as a semantic segmentation approach to identify regions of interest within the image. The U-Net model capitalizes on fully convolutional networks, aiming to capture contextual and localization features. The architecture of the U-Net model comprises two pathways. The initial pathway, referred to as the contraction path or encoder, is employed to capture the contextual information of the image. This encoder segment uses a conventional sequence of max pooling and convolutional layers [288]. The subsequent pathway, also known as the decoder, functions symmetrically to the expanding path, facilitating precise localization through transposed convolutions. The U-Net is an end-to-end fully convolutional network (FCN), rendering it capable of processing images of varying dimensions. Notably, the U-Net model exclusively employs Convolutional layers, omitting the use of Dense layers [289].

Within the scope of this study, image segmentation is employed to distinguish the tomato images from their respective backgrounds, forming the foundation for subsequent image processing tasks.

b. Image Cropping

Every individual tomato image is initially transformed into the RGB format, paving the way for subsequent processing. The RGB format images undergo a refinement process to minimize potential noise while diminishing the image's dimensionality, thereby bolstering the overall processing efficiency. Employing the Otsu image thresholding technique, the RGB images are subjected to binarization based on the pixel intensities [290]. This method determines the threshold value at which the weighted variance between foreground and background pixels attains its minimum value. However, it is noteworthy that complete elimination of the background is not always achieved in certain tomato images. Consequently, a cropping operation is conducted to extract the tomato component from the entirety of the image.

5.2.3 Manual Feature Extraction

Manual extraction of features is conducted on the tomato images to derive color, texture, and shape attributes, as visually represented in Figure 5.1. The manually extracted features integral to the proposed approach are comprehensively detailed in Table 5.2.

a. Color Features

The color features, classified as first-order statistical features, encompass measures of spatial statistics and are derived within the LAB (Lightness (L), Red to Green (A), and Yellow to Blue (B))color space framework, a choice made in this study. The LAB color space is characterized by a three-axis color system with predefined ranges for its dimensions: L, A, and B. In this context, L signifies brightness, where $L = 1$ denotes the brightest white and $L = 0$ indicates the darkest black. On the other hand, A and B correspond to color channels. The LAB color space accommodates the entire spectrum of colors, even those imperceptible to the human eye [291]. Three distinctive color features—mean, range, and standard deviation—are extracted from this LAB color space. These features capture characteristics of the color distribution within the image. It is important to note that these color attributes solely rely on individual pixel values and do not account for the relative relationships between different grey levels [164].

b. Texture Features

The next category of features pertains to texture attributes, constituting second-order measures. These attributes involve examining paired grey values among pixels, effectively capturing the spatial interdependency of grey levels. To achieve this, applying GLCM (Gray-Level Co-occurrence Matrix) is employed in this study to calculate Haralick's textural characteristics [292]. Given that defects lack a distinct orientation, each image is represented as a two-dimensional GLCM matrix. To obtain an aggregated representation of the matrix's textural properties, averaging is performed within the proximity of a distance parameter, denoted as d = 1, along four directional angles: 135°, 90°, 45°, and 0°.

The extracted textural attributes encompass contrast, energy, correlation, entropy, and homogeneity. As depicted in Figure 5.1, these features provide insights into the texture variations within the images.

c. Shape Features

The contouring process is employed on the binarized image to ascertain the tomato's shape. In this context, contours serve as the delineations outlining the image's boundaries. They are formed by tracing the edges, allowing for the extraction of geometric and structural characteristics. Consequently, this approach facilitates the retrieval of the image's dimensions, which, in turn, serves as a feature crucial to subsequent processing steps.

Table 5.2. Manual Features Extracted for Tomato Ripeness Evaluation

Manual Features	Description
Color Features (LAB color features, Mean, Range, Standard Deviation)	**LAB color features:** LAB color features are a color space that separates the luminance (brightness) component (L) from the chromatic components (A and B), making it valuable for tasks like color correction, image analysis, and color-based object recognition. **Mean:** It quantifies the average color intensity within an image or region of interest. **Range:** It measures the spread or variability of colours within an image or a specific region, providing insights into color diversity. **Standard Deviation:** It assesses the degree of color variation or dispersion in an image, aiding in color analysis and characterization.

Texture Features (Contrast, Energy, Correlation, Entropy, and Homogeneity)	**Contrast:** It quantifies the difference in brightness or color between adjacent pixels, providing information about texture patterns in an image. **Energy:** It represents the uniformity or presence of specific texture patterns in an image, calculated from the distribution of pixel intensities **Correlation:** It assesses the linear relationship between pixel intensities in different directions, indicating the texture's level of symmetry or regularity. **Entropy:** It quantifies the randomness or disorder of pixel intensities within a texture, providing information about its complexity. **Homogeneity:** It measures the similarity of pixel intensities in an image, indicating the uniformity or consistency of the texture.
Shape Features (Image Size)	**Image Size:** It represents the physical dimensions of an image or object, such as its width and height, providing basic size information.

5.2.4 Feature Extraction via CNN

Image embedding is a fundamental component of the image analysis process, forming an integral part of the framework of the image processing model. Within this context, the Inception V3 deep learning image recognition model is harnessed for feature extraction. Inception V3, an extension of the Google Net CNN architecture, emerges as a profound 42-layer deep CNN model from the Inception family, specifically referred to as Inception-V3 [293]. This model is structured with an array of symmetric and asymmetric construction blocks, incorporating advancements such as enhanced 7 x 7 convolutions, label smoothing, average pooling, max pooling, concatenated and dropout layers, fully connected branches, and auxiliary classifier label information. Collectively, these innovations work to minimize network size while optimizing performance.

The Inception V3 model efficiently generates feature vectors from individual tomato images. The activation inputs are subjected to batch normalization, a widely utilized technique throughout the model [294]. The softmax function is employed to calculate the loss. A comprehensive overview of the layers within the Inception V3 architecture is elucidated in Table 5.3. In addition, PCA feature selection is applied to get the essential features from the obtained feature vector, as shown in Figure 5.1. Minimizing redundant information and removing ineffective minor components decreases dimensionality [295]. It converts feature spaces of samples into feature sub-spaces (smaller spaces that contain all independent variables required to explain the data) by eliminating all ineffective minor components. In this study, PCA has been applied to the feature vectors generated by the Inception V3 model. PCA has been used due to its ability to reduce dimensionality, eliminate noise, enhance computational efficiency, improve generalization, and aid in visualization and interpretability. By focusing on the most significant features, PCA ensures that the model is both efficient and effective, providing robust performance in the task of the tomato quality prediction model.

Table 5.3. Network of Layers in Inception V3

Layer Type	Patch/Stride Size	Input Dimension
Convolution Layer	$3 \times 3/2$	$299 \times 299 \times 3$
Convolution Layer	$3 \times 3/1$	$149 \times 149 \times 32$
Convolution Layer Padded	$3 \times 3/1$	$147 \times 147 \times 32$
Pooling Layer	$3 \times 3/2$	$147 \times 147 \times 64$
Convolution Layer	$3 \times 3/1$	$73 \times 73 \times 64$
Convolution Layer	$3 \times 3/2$	$71 \times 71 \times 80$
Convolution Layer	$3 \times 3/1$	$35 \times 35 \times 192$
3×Inception	$3 \times 3/2$	$35 \times 35 \times 288$
5 ×Inception		$17 \times 17 \times 768$
2×Inception		$8 \times 8 \times 1280$
Pooling Layer	8×8	$8 \times 8 \times 2048$
Linear	Logits	$1 \times 1 \times 2048$

The PCA transforms the original data into a lower-dimensional space as follows in equation (5.1).

$$Y_{new} = Y_{original} \cdot M \tag{5.1}$$

where:

- Y_{new} is the data in the new space, which is of reduced dimensionality.
- $Y_{original}$ is the data in the original space, which has higher dimensionality.
- M is the matrix of the principal components.

The PCA process effectively reduces the dimensionality of the data by transforming it from the original space to the space defined by the principal components. The transformation is done linearly, as indicated in the equation, and it helps retain the most significant information while reducing redundancy and noise in the data.

5.2.5 Machine Learning Models for Regression

The different machine learning models are used to train the proposed model. The regression is applied specifically as the aim is to predict the ripeness value of the tomato. The details of these models are as follows.

a. Support Vector Machine (SVM)

SVM is a popular statistical classification and regression technique based on a supervised learning algorithm. In supervised learning methods, a high-dimensional feature space is typically used as the nonlinear input for vectors. The algorithm uses the construction risk minimization principle to find the highest margin in the n-dimensional feature space to find the ripeness of the tomatoes [296]. The present work explores various kernel functions, including radial basis, cubic, quadratic, and linear. The efficiency and accuracy of an SVM regressor are both impacted by the choice of the kernel function [297].

b. Decision Tree (DT)

The DT classifier is instrumental in both regression and classification tasks. This classifier predicts the target variable by analyzing feature data and partitioning regions into smaller segments. The process of division hinges upon impurity measurement and information gain metrics. In our dataset, DT employs the "Gini" impurity metric to divide nodes, identifying the one that yields the most substantial information gain. In the context of the Tomato image dataset, the splitting criteria are contingent upon distinct image features. The iterative division continues until leaf nodes can no longer be further partitioned, thus capturing every possible piece of information.

c. Random Forest (RF)

Random Forest is a supervised machine learning algorithm that yields classification and regression outcomes by aggregating decisions from multiple trees. These decision trees are crafted based on randomly chosen data samples, with the ensemble subsequently gathering predictions from each tree and then consolidating them via a voting mechanism to determine the final outcome. This approach finds its roots in the Boruta algorithm, identifying significant features within the tomato database. Essentially, a random forest operates as an ensemble of decision trees, generated on subsets of the dataset, resulting in a comprehensive and effective modelling process. During the decision tree creation, the algorithm relies on indicators such as the gain ratio, Gini index, and information gain for each characteristic to facilitate feature selection. This entails selecting the most influential features to construct the decision trees, enhancing the model's predictive capability. Notably, the random forest process entails the use of distinct random samples for each tree branch, which further diversifies the model's perspectives. In the classification scenario, each tree contributes a vote during categorization, collectively determining the optimal class. Conversely, in regression, the final output is the mean of the outcomes generated by all the individual trees. One of the notable attributes of the random forest approach is its feature selection metric, which assigns each feature a relevance score during model training. This aspect proves valuable in assessing the importance of each feature, thus aiding in model interpretation and optimization.

d. Gradient Boosting Method (GBM)

Gradient boosting is a category of ensemble machine learning techniques extensively employed for addressing classification and regression predictive modelling challenges. At its core, this algorithm is rooted in the concept of "boosting," which amalgamates the predictions from "weak" learners to cultivate a potent "strong" learner through a series of additive training strategies. Within this approach, decision tree models form the basis of ensembles, with each tree progressively integrated to address prediction errors made by previous models.

The hyperparameter values for distinct machine learning models are determined through an iterative process involving training models with various parameter values. Subsequently, the models exhibiting the lowest error for the given parameters are chosen for implementation in the proposed framework. A comprehensive details of the fine-tuned hyperparameters for diverse regression models is conveniently organized in Table 5.4.

Table 5.4. Hyperparameter Values for the Regression Models

Model	**Hyperparameter Values**

SVM	`kernel: rbf`
	`degree:2`
	`c: 5`
	`gamma: auto`
	`coef0: 0.01`

DT	`criterion=squared_error`
	`max_depth=10`
	`max_features=auto`

	`splitter=best`

RF	`criteria: squared_error`
	`n_estimators: 500`
	`verbose: 3`

GBM	`criteria: mse`
	`learning_rate:0.01`
	`loss: squared_error`
	`max_depth:10`
	`n_estimators: 500`

5.3 Metrics used for Evaluation of Tomato Quality Prediction Model

The results of the machine learning models are evaluated using various important regression parameters discussed as follows. These metrics offer insights into the magnitude and distribution of prediction errors.

- $Mean\ Square\ Error(MSE)$: The mean or average of the squared discrepancies between the anticipated and expected target ripeness values in the tomato dataset is used to calculate the MSE. It is calculated as equation(5.2).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_a - x_p)^2 \tag{5.2}$$

where x_a is the actual ripeness value of the i_{th}tomato and x_p is the predicted ripeness value of the i_{th}tomato for n tomato samples.

- $Root\ Mean\ Square\ Error(RMSE)$: The square root of the mean of the squared discrepancies between the anticipated and expected target ripeness values in the tomato dataset is used to calculate the MSE. It is calculated as equation (5.3).

$$RMSE = \sqrt{MSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_a - x_p)^2} \tag{5.3}$$

where x_a is the actual ripeness value of the i_{th}tomato and x_p is the predicted ripeness value of the i_{th}tomato for n tomato samples.

- $Mean\ Absolute\ Error\ (MAE)$: It is calculated as the average of the absolute difference between the target and predicted ripeness values of the tomato. It is defined as equation (5.4).

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|x_a - x_p| \tag{5.4}$$

where x_a is the actual ripeness value of the i_{th}tomato and x_p is the predicted ripeness value of the i_{th}tomato for n tomato samples.

- $R\ Square(R^2)$: R-squared indicates how much the variation of one variable contributes to the variance of the second. In other words, it calculates the percentage of the variance of the ripeness value of the tomato that can be accounted for by the independent variables. It is calculated as equation (5.5).

$$R^2 = 1 - \frac{SSE}{SST} \tag{5.5}$$

where SSE is the sum of the square of the difference between the actual value and the predicted value, and SST is the sum of the square of the difference between the actual value and the mean of the actual value. They are calculated as equation (5.6) and equation (5.7).

$$SSE = \sum_{i=1}^{n} (x_a - x_p)^2 \tag{5.6}$$

$$SST = \sum_{i=1}^{n} (x_a - \overline{x_a})^2 \tag{5.7}$$

where x_a is the actual ripeness value of the i_{th}tomato, x_p is the predicted ripeness value of the i_{th} tomato and $\overline{x_a}$ is the actual mean value of the ripeness of the tomato for n tomato samples.

- $P\ Value\ (p)$: P Value is the probability value that determines the significance of the results in relation to the null hypothesis. Since the data is not normally distributed in our case, Levene's test calculates the p value to assess the equality of the variance for the ripeness value from different groups. It evaluates the null hypothesis that the variances in the population are equal. The obtained disparities in sample variances are unlikely to have occurred based on random sampling from a population with equal variances if the resulting p value of Levene's test is less than some significance level (usually 0.05) [298]. Consequently, it is concluded that a distinction exists in population variances, thus invalidating the null hypothesis of uniform variances.

5.4 Results of the Tomato Ripeness Prediction on Extracted Features

The model undertakes the prediction of ripeness by leveraging machine learning regression techniques expounded upon in the preceding section. The approach adapts diverse preprocessing methods tailored to address the specific image challenges found within the database, thereby extracting distinctive features from the processed images. Three distinct models are considered, aiming to introduce diversity at both the feature and data levels as they predict tomato ripeness. These models encompass prediction based on manually extracted features, automated features, and a fusion of both manual and automated features. Numerous machine learning models are experimented with during the process of model development. However, only those demonstrating notable high performance are retained. In this context, SVM, RF, DT, and GBM machine learning methods are harnessed to train the regression models. The division of data for training and testing purposes adheres to a 70:30 ratio.

The regression outcomes pertaining to diverse features are meticulously explored in the ensuing sub-sections.

a. Results of Ripeness Prediction on Manually Extracted Features

The manually extracted features are used to train the model to predict the ripeness of the tomatoes. The preprocessed tomato images are used as input to train the different machine-learning models with hand-crafted features for regression. The discussed machine learning methods are used to prepare models with manual features. The color features include LAB color features, texture features include GLCM texture features, and the image size is the input parameter to train the model for different machine learning methods. The description of the features is mentioned in Table 5.2. In total, 13 manually extracted features are used to train the model to predict the ripeness of the tomato. The regression results for manually extracted features are presented in Table 5.5.

Table 5.5. Regression Results for Manual, Automated and Combination of Manual and Automated Features

	Model	MSE	$RMSE$	MAE	R^2	$p\ value$
Manual Features	SVM	1.06	1.02	0.76	0.69	0.02
	DT	1.4	1.18	0.82	0.64	0.20
	RF	0.88	0.93	0.71	0.74	0.02
	GBM	1.04	1.01	0.74	0.71	0.03
Automated Features	SVM	1.56	1.24	0.73	0.42	0.02
	DT	1.43	1.19	0.84	0.63	0.21
	RF	0.87	0.93	0.71	0.73	0.02
	GBM	0.96	0.97	0.73	0.71	0.03
Combination of Manual and Automated Features	SVM	1.3	1.14	0.87	0.73	0.02
	DT	1.3	1.14	0.81	0.64	0.20
	RF	0.88	0.93	0.72	0.73	0.02
	GBM	1.04	1.01	0.75	0.69	0.03

b. Results of Ripeness Prediction on Automated Features

The automated extracted features from the Inception V3 model are used to train the model for ripeness prediction of the tomato and further classify them based on their utility. The 2048 automated features are obtained from the deep learning model. These physical features of the tomato are the image descriptors and dimensional representation of the images. The PCA feature selection method chooses the 50 crucial features from the obtained parameters. PCA finds linear combinations of the original features that retain most of the variance in the data. These linear combinations are the principal components, and they define a transformation that maps the original 2048-dimensional space to a lower-dimensional space (50 dimensions). The transformation is done linearly to retain the most significant information while reducing redundancy and noise in the data. The model is prepared by training ML models with 50 automated features as input to get the tomato ripeness as the output. As mentioned in equation (5.1) Y_{new} is a matrix where each row corresponds to an observation or data point, and each column corresponds to a principal component. The values in this matrix represent the data transformed into the lower-dimensional space with 50 dimensions. $Y_{original}$ is a matrix where each row corresponds to an observation or data point, and each column corresponds to one of the original features. This matrix contains the original, high-dimensional data with 2048 dimensions. M is the matrix of the 50 principal components. Each column in this matrix represents one of the principal components, and PCA calculates these components in such a way that they capture the maximum variance in the original data. The regression results for automated extracted features are described in Table 5.5.

c. Results of Ripeness Prediction on Combined Features

A fusion of manually and automatically extracted features is combined to train a set of machine learning (ML) models, culminating in creating a fusion model to predict tomato ripeness. This comprehensive approach entails utilizing a collective 63 features (13 manual features and 50 automated features) as input, generating ripeness predictions as the corresponding output. The regression outcomes concerning the tomato's ripeness in relation to these combined features are meticulously detailed in Table 5.5.

5.4.1 Interpretation of Results for Tomato Ripeness Prediction on Extracted Features

As observed from Table 5.5, the $p\ value$ for DT is not in the acceptable range (<0.05) for manual, automated, and combination of manual and automated features. The $p\ value$ is significant only if it is below 0.05. Hence, the DT is eliminated from the final ensemble model due to its poor statistical significance. The other parameters MSE, $RMSE, MAE$ provide insights into the magnitude and distribution of prediction errors for the tomato ripeness values. In the proposed model, MAE is the most important parameter of error prediction analysis as we are interested in the balanced view of tomato ripeness prediction performance without considering outliers.

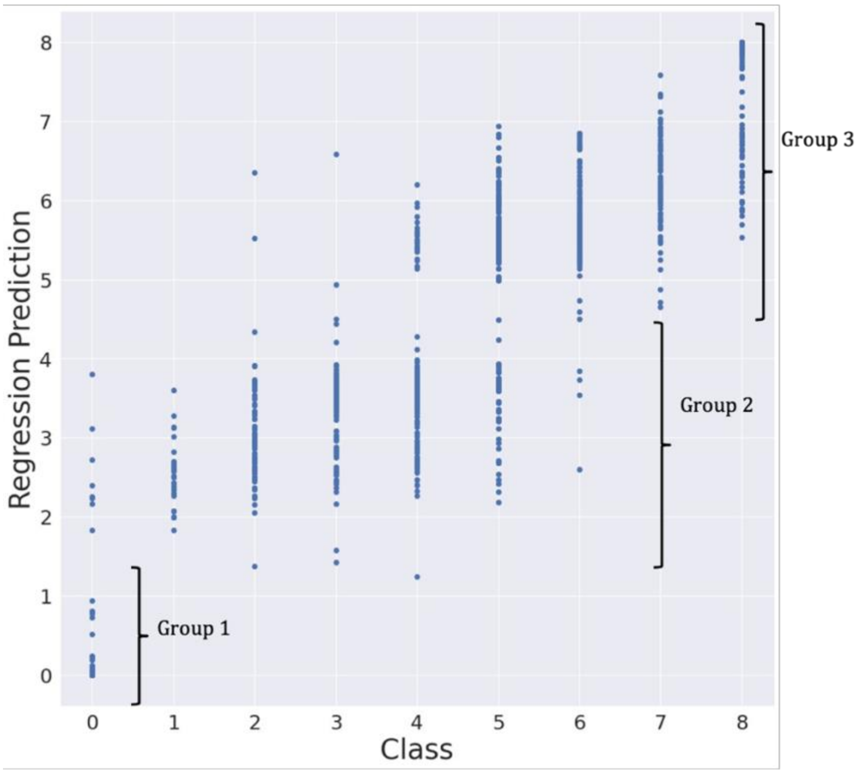


Figure 5.3. Class Division of Tomato samples based on Regression

The value of MAE is below 1 for all the models and that of MSE, and $RMSE$ also lie approximately between 0-1.5 for the ML models. The value of (R^2) represents the goodness of fit, i.e., it tells how well the data fits the regression model. In the proposed model, the value of R^2 is almost lying between 0.5 to 1 around 60% - 75% for all the models, which is good enough for consideration. The division of the tomato samples in the testing data as per the regression model for combined features is plotted in Figure 5.3. It represents how the tomato samples are categorized for the ripeness values 0-8. Evidently, the data aggregates into three distinct clusters. The robustness and effectiveness of the model become apparent through the process of ensemble, wherein multiple machine learning models collaborate to yield the final output decision.

5.4.2 Proposed Ensemble Approach

The presented model anticipates both the ripeness and shelf life of tomatoes by integrating various machine-learning regression methods. Employing an ensemble approach, the model leverages various features and regression techniques, ensuring a comprehensive and diverse methodology. The preprocessing of images is carried out, effectively addressing outliers within the images, as it performs ripeness prediction on the tomato dataset. The ensemble aspect of the proposed technique necessitates distinctiveness. Hence, a selection of expert base regressors is employed. This process fosters diversity in features and data at different levels, incorporating various preprocessing, feature extraction, and selection methodologies. As visualized in Figure 5.4, the ensemble regression technique meticulously assesses features and data models.

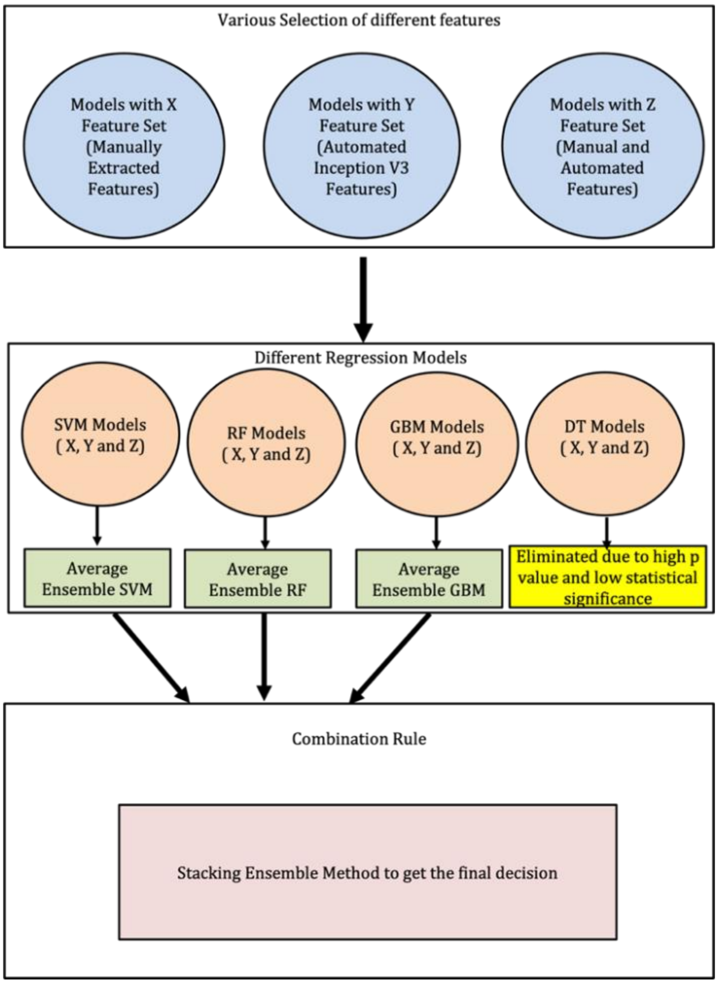


Figure 5.4. Ensemble Strategy for Tomato Ripeness Prediction

Subsequently, the stacking technique comes into play to finalize the prediction process. The findings reveal that a blend of diverse preprocessing methods, multiple parameters, and adept machine learning regressors can introduce considerable diversity within the proposed ensemble methodology, thereby bolstering accuracy in contrast to conventional machine learning and deep learning models. Consequently, the suggested procedure unfolds in three successive steps:

Step 1: Diverse preprocessing methodologies are employed, accompanied by feature extraction and selection approaches, each tailored to address specific issues within the image database.

Step 2: An array of regression models is explored, contributing to developing diverse machine-learning models.

Step 3: A combination rule is applied to synergize the predictions.

The recommended strategy integrates various preprocessing techniques, adapting them to cater to distinct challenges inherent in the image database. This integration extracts manual and automated characteristics from preprocessed images using an ensemble approach.

The ensuing segments elaborate on the three distinct feature sets implemented to foster diversity at both the feature and data levels:

- *Feature Set X*: Representing machine learning models founded upon manually extracted features, Feature Set X encompasses four machine learning models that employ such features, as illustrated in Figure 5.4.
- *Feature Set Y*: Encompassing machine learning models based on features automatically extracted from the Inception V3 model, Feature Set Y comprises models with 50 automated features as inputs, subsequently predicting tomato ripeness as the output.
- Feature Set Z: Comprising machine learning models originating from the amalgamation of manual and automated extracted features, Feature Set Z comprises 63 features as inputs to anticipate ripeness. Figure 5.4 further illustrates the four machine-learning models relying on manual and automated features.

Ensemble Models: The three feature set models have been trained using four machine-learning regression models. In total, 12 different ML models have come up after training. The ensemble model in each of these cases is prepared using the average ensemble method to get the best ML model that predicts the ripeness of the tomato. The average ensemble method in ML involves training multiple models independently and combining their predictions by taking an average. This technique enhances predictive accuracy, reduces overfitting, and improves model robustness, making it a common approach for better generalization and stability. The average ensemble shows up with three ensemble models, namely Ensemble SVM, Ensemble RF, and Ensemble GBM with manual, automated and a combination of manual and automated features. The DT is not considered for the Ensemble model as the p value of the model is not less than 0.05, unlike the other machine learning models, and does not statistically contribute to model significance. The final ripeness values are predicted by averaging the values of each of the regression models individually.

Stacking Proposed Ensemble Model: The usability of tomato fruit hinges on its shelf life within the temperature range of 12°C to 24°C. It is a well-established fact that tomato storage life fluctuates with temperature. Analyzing data points in Fig.5.3, the output of ML models categorizes ripeness into three classes based on ripeness index and color-magnitude. Class 0 (Group 1) pertains to tomatoes designated for *storage*, while Class 1 (Group 2) and Class 2 (Group 3) correspond to *sale categories without and with discounts*, respectively. This classification is realized through an ensemble stacking method. Specifically, stacking is employed among three machine learning methods – Ensemble SVM, Ensemble RF, and Ensemble GBM – to effectively categorize tomatoes into the aforementioned output classes, thus predicting tomato shelf life. Stacking is an ensemble technique that guides the model in combining predictions from learner models and meta-models to formulate a conclusive model with accurate predictions. The shelf life of tomatoes is determined using a random forest regressor, which incorporates the output of average ensemble models. The outcomes of the proposed model are delineated in the subsequent section.

5.4.3 Results of the Proposed Ensemble Model

The outcomes of the models predicting tomato shelf life, derived through the averaging of ensembles, are showcased in Table 5.6. The output of the average ensemble models is used along with a random forest regressor as a stacking model to identify the ripeness of the tomato. The Random Forest Regressor captures complex interactions among base model predictions, providing enhanced predictive power, robustness, and handling high-dimensional data effectively. The evaluation metrics used for the tomato shelf-life classification model are discussed below.

- $Accuracy\ (A)$: It measures the proportion of correctly predicted instances out of the total number of instances in a dataset as defined in equation (5.8)

$$Accuracy(A) = \frac{TP + TN}{TP + TN + FP + FN} \tag{5.8}$$

- $Precision\ (P)$: The precision is given as a ratio of true positive predictions out of all positive predictions made by the model as defined in equation (5.9)

$$Precision(P) = \frac{TP}{TP + FP} \tag{5.9}$$

- $Recall\ (R)$: Recall measures the model's ability to identify all relevant instances of the positive class. It calculates the proportion of true positive predictions out of all actual positive instances as defined in equation (5.10)

$$Recall(R) = \frac{TP}{TP + FN} \tag{5.10}$$

where TP: True Positive, FP: False Positive, FN: False Negative

- $F1\ Score$: The F1 Score calculates the harmonic mean of precision and recall, as outlined in the equation provided (5.11).

$$F1\ Score = \frac{2.P.R}{P + R} \tag{5.11}$$

The conclusion drawn emphasizes the prioritization of precision over recall within the proposed model, driven by the objective to minimize false positive errors. As Table 5.6 indicates, the precision value for class 0 (Store class) is comparatively lower than that of the other classes. It is mainly due to the low number of samples in this class, as evident from the observation in Figure 5.3. The confusion matrix of the stacking proposed ensemble model is depicted in Figure 5.5

Figure 5.5. Confusion Matrix for Stacking Proposed Ensemble Model

Table 5.6. Results of the Tomato Utility Prediction Models

Model	**Overall Accuracy (%)**	**Precision Class 0 (%)**	**Precision Class 1 (%)**	**Precision Class 2 (%)**	**Average Precision**	**Recall Class 0 (%)**	**Recall Class 1 (%)**	**Recall Class 2 (%)**	**Average Recall**	**F1 Score Class 0 (%)**	**F1-Score Class 1 (%)**	**F1-Score Class 2 (%)**	**Average F1 Score**
Ensemble SVM	87.63	50.52	91.91	90.97	77.80	100	79.78	93.61	91.13	67.13	85.42	92.27	81.61
Ensemble RF	89.56	63.15	93.38	91.35	82.63	100	82.46	94.73	92.40	77.41	87.58	93.01	86.01
Ensemble GBM	89.08	64.21	93.13	90.41	82.58	100	81.72	94.49	92.07	78.20	87.05	92.41	85.89
Stacking Proposed Ensemble Model	90.35	62.06	93.49	93.08	82.88	94.73	83.94	95.48	91.38	75.00	88.46	94.26	85.90

5.4.4 Testing of the Proposed Ensemble Model

The proposed tomato shelf life prediction model has been applied to identify sample images.

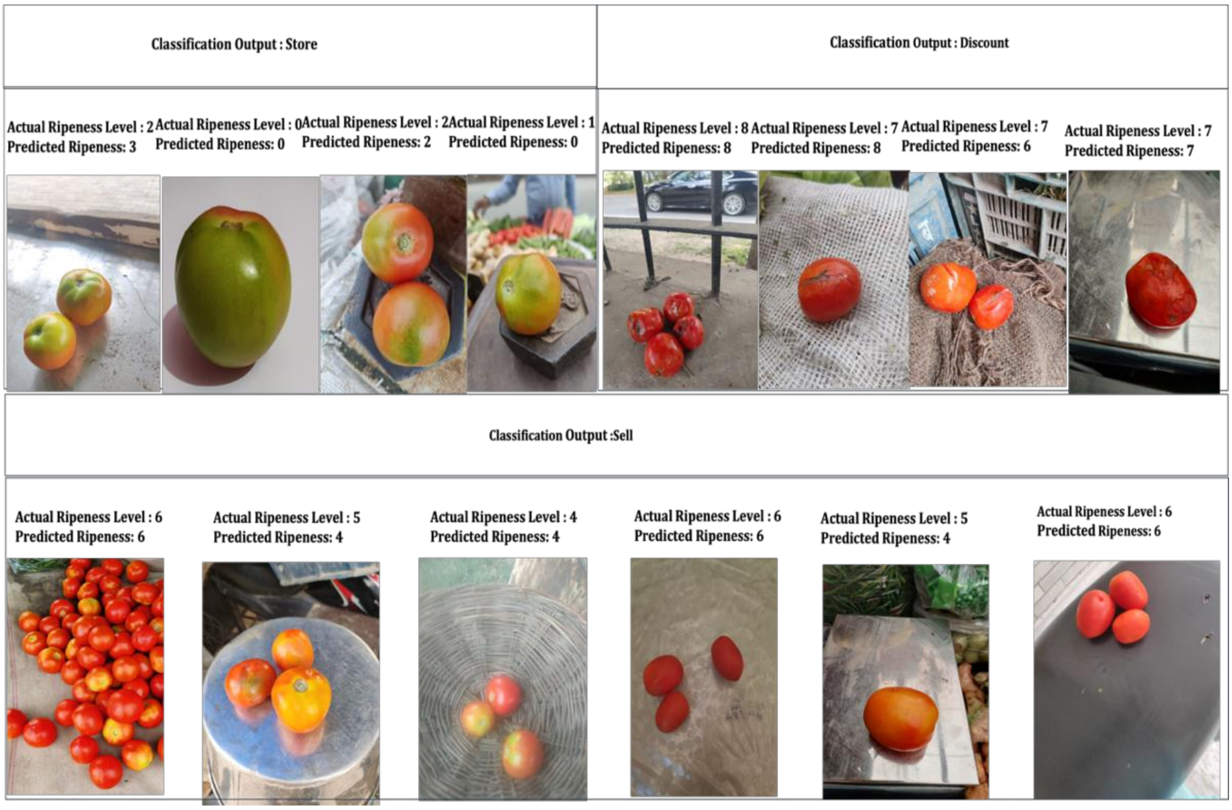


Figure 5.6. Testing Images of Tomato Shelf Life Prediction Model

The performance of the model is evaluated using images from the test set that are not included in the training phase. These samples encompass diverse scenarios, captured by users utilizing a basic mobile camera. The scenarios include complex backgrounds and images of varying camera resolutions (high and low quality). When presented with an input image, the model predicts the ripeness level of the tomato image, based on which it is assigned to a specific output class to identify the shelf life. As per the division of tomato data in Figure 5.3, the store class is assigned to the unripe tomatoes, the sell class is for ripe or medium ripe, and the discount is for rotten or defective tomatoes. The results of the model on various samples are shown in Figure 5.6.

5.4.5 Comparison of the Proposed Tomato Quality Detection Model with the existing state-of-the-art methods

As evidenced in the existing literature, researchers have extensively employed machine learning and deep learning techniques to assess the ripeness of tomato fruits. To gauge the efficacy of the proposed model for tomato ripeness and utility prediction, a comparative analysis is conducted against prevailing state-of-the-art methodologies.

Srivastav et al. (2014) [299] developed a vision-based system, achieving a tomato quality detection accuracy of 92%. Blendary et al. (2015) [295] introduced a multi-classification approach to categorize tomatoes based on ripeness stages, attaining an accuracy of 90.80%. Zhang et al. (2018) [300] harnessed deep-learning classification to evaluate tomato ripeness, yielding an accuracy of 91.9%. Employing an SVM classifier, Garcia et al. (2019) [301] accomplished tomato ripeness identification with an accuracy of 83.39%, while the proposed model achieved 90.35% accuracy.

Liu et al. (2019) [302] proposed an automated tomato detection method in color images with precision, recall, and F1 score values of 94.41%, 90.00%, and 92.15%, respectively. In contrast, the proposed model exhibits recall, precision, and F1-Score values of 91.38%, 82.88%, and 85.90% respectively.

Kim et al. (2022) [303]devised a deep neural network approach to estimate tomato maturity, yielding an average F1 Score of 91%. In comparison, the proposed model demonstrates an F1-Score of 85.90%. Evidently, the results achieved by the proposed model align favorably with those of the current state-of-the-art methodologies.

Chapter Summary

The primary objective of this research was to develop a predictive model for assessing the ripeness and usability of tomato fruits. The database employed for this purpose consists of labelled images, categorized according to the ripeness index, determined through color-magnitude analysis. Diverse image preprocessing techniques were implemented to address image anomalies like noise, background clutter, shadows, and brightness fluctuations. Furthermore, an assortment of features was extracted from the images, encompassing manually derived attributes and automated features. Manual feature extraction involved capturing color, texture, and shape characteristics, whereas automated attributes were obtained using the Inception V3 model. For the regression aspect, various machine learning models – SVM, DT, RF, and GBM – were employed as regressors, leveraging manual features, automated features, and a fusion of both to predict the ripeness index of the tomatoes. Subsequently, the tomatoes were categorized to find their usability. The proposed model underwent optimization via the Stacking Ensemble Learning technique, ultimately facilitating the determination of tomato shelf life. Therefore, understanding and extending the shelf life of tomatoes is essential for preserving freshness, reducing waste, and optimizing supply chain efficiency. Accurate predictions of shelf life enable better inventory management, ensuring that tomatoes are harvested, transported, and consumed at their peak quality. This benefits consumers by providing fresher produce, minimizing food waste, and supporting sustainable agricultural practices. The outcomes indicate that the proposed approach effectively realizes the prediction of tomato ripeness and usability on the validation dataset. Future endeavours could involve broadening the dataset scale to enhance generalizability. Additionally, there's potential for deploying a mobile application for end users, facilitating predictions regarding tomato shelf life.

Chapter 6

Real-Time AI Enabled IoT Based Milk Adulteration Detection System

Milk, a rich source of essential minerals, proteins, and vitamins, holds a significant place in the diets of individuals worldwide. The volume of cow milk produced worldwide has risen steadily over the last several years. In 2015, 497 million metric tons of cow milk was produced worldwide. By 2023, that figure had risen to around 549 million metric tons. India stands as the leading global milk producer, contributing to 24% of the total milk production [304]. With a compound annual growth rate of approximately 5%, milk production in India has surged to 221.06 million tonnes in the fiscal year 2022 [305]. However, the escalating demand for milk and its products has led certain vendors to resort to unethical practices, such as adulteration, to meet the supply-demand gap. The adulteration of milk gained global attention since the discovery of melamine particles in imported milk products in 2008 [306]. Unscrupulous practices involve the addition of adulterants to increase volume, mask subpar quality, and engage in illicit profiteering. Adulterants such as water, detergents, caustic soda, urea, and glucose are often incorporated, compromising nutritional value and posing health risks [307]. Chemicals like chlorine, sodium carbonate, lime, and starch further aggravate the problem [308]. Consumption of adulterated milk can lead to various illnesses, hospitalizations, and even fatalities, including renal failures in both adults and infants.

In light of these alarming health concerns, there is an urgent need for an efficient system to detect milk adulteration. Current detection methods, such as Fluorescence Spectroscopy and Impedance Analyzers, are expensive and unsuitable for home-based testing [104], [309]. Developing and validating new analytical procedures are essential to enable prompt and accurate detection and quantification of adulteration. Driven by the increasing demand for reliable adulteration detection methods, health organizations and researchers worldwide are investing substantial efforts in intelligent technology research. Technological advancements offer the potential for creating cost-effective and user-friendly devices. Qualitative and quantitative methods are utilized for detecting milk adulteration, with qualitative methods relying on multiple chemical reactions and quantitative methods allowing the identification of specific adulterants. The convergence of Internet of Things (IoT) technologies with spectroscopic and other sensor types presents a potent toolkit for assessing milk quality and authenticity [299]. This study proposes a low-cost IoT-based system employing machine learning (ML) techniques for detecting milk adulteration.

The chapter aims to contribute to the development of swift and accurate machine-based methods for combating milk adulteration, thereby ensuring the well-being of consumers and bolstering the dairy industry's integrity.

6.1 Contribution

The present study explores the utilization of an AI-enabled, cost-effective system comprising IoT-based sensors to detect adulteration in raw milk. The investigation explicitly evaluates the detection of five adulterants, starch, urea, formaldehyde, sodium bicarbonate, and maltodextrin, at distinct adulteration ratios.

A comprehensive dataset is generated by developing an IoT-based framework incorporating diverse sensors to facilitate this research.

6.2 Materials and Methods

In this research, a novel AI-enabled IoT sensor system with an affordable design is proposed to detect milk adulteration. The architecture of the proposed framework is depicted in Figure 6.1, providing a comprehensive overview of its components and functionalities.

The subsequent sections of the paper extensively explore the experimental setup, which involves the preparation of samples, the data collection process, and the application of a machine learning ensemble approach for data analysis.

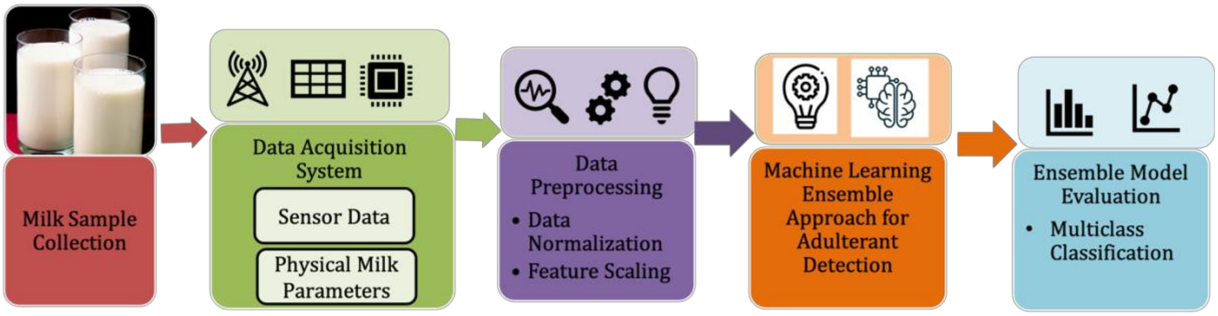


Figure 6.1 Proposed Architecture of Milk Adulteration Detection System

It elaborates on the step-by-step procedure of the experiment, showcasing the AI-enabled IoT sensor system's efficacy in real-time detection of milk adulteration and its potential for ensuring milk quality and safety.

6.2.1 Design of Real-time AI-based sensor system for milk adulteration detection

A Real-time AI-enabled low-cost IoT-based multi-sensor system is meticulously developed. The design incorporates a Wireless Module (ESP32), Arduino UNO microcontrollers, and diverse sensors to facilitate data acquisition. The microcontroller utilized in the system is 5V-compatible. It boasts an integrated Wi-Fi module, enabling seamless transmission of sensor data to an online cloud server for real-time monitoring and analysis. The representation of the data acquisition system is presented in Figure 6.2, illustrating the interconnected blocks and components within the system.

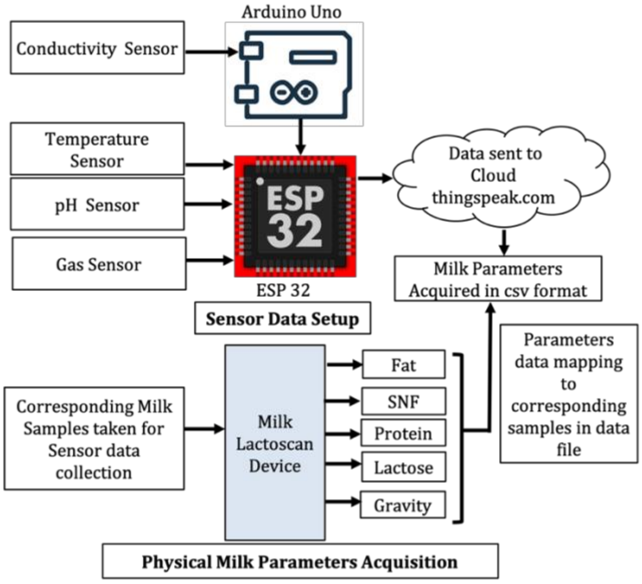


Figure 6.2 Block Diagram of Milk Data Acquisition System

To experiment, the multi-sensor system efficiently gathers milk samples. It carefully selects specific types of adulterants mixed into raw, pure milk to replicate real-world scenarios of milk adulteration. The proposed milk adulteration detection method utilizes a combination of sensors to detect essential parameters such as pH, temperature, conductivity, and Volatile Organic Compounds (VOC). In parallel, the physical parameters such as Fat, Protein, Solids-not-Fat (SNF), Lactose, and Gravity values are simultaneously collected for the milk samples using a standard Lactoscan device. The selection of sensors considers both their cost-effectiveness and efficiency, with the details provided in Table 6.1.

Table 6.1. Details of the Components of the Milk Data Acquisition System

Physical Parameter	**Source of data** [310]	**Normal Range to keep milk Fresh** [311]-[313]
pH	DFROBOT Analog pH sensor	6.4-6.9
Temperature	DS18B20t temperature sensor	15°C -25°C for room temperature

Conductivity	DFROBOTICS analog electrical conductivity	2.5 to 5 ms/cm at 18°C
VOC	MQ135	-
Fat	Lactoscan Milk Analyzer SL30	5.5% -8.5%.
SNF	Lactoscan Milk Analyzer SL30	4.5% fat, 8.5% SNF, and 13% total solids.
Protein	Lactoscan Milk Analyzer SL30	3.6%
Lactose	Lactoscan Milk Analyzer SL30	5.48%
Specific Gravity	Lactoscan Milk Analyzer SL30	the specific gravity of milk is usually given at 15.6°C (60° F)

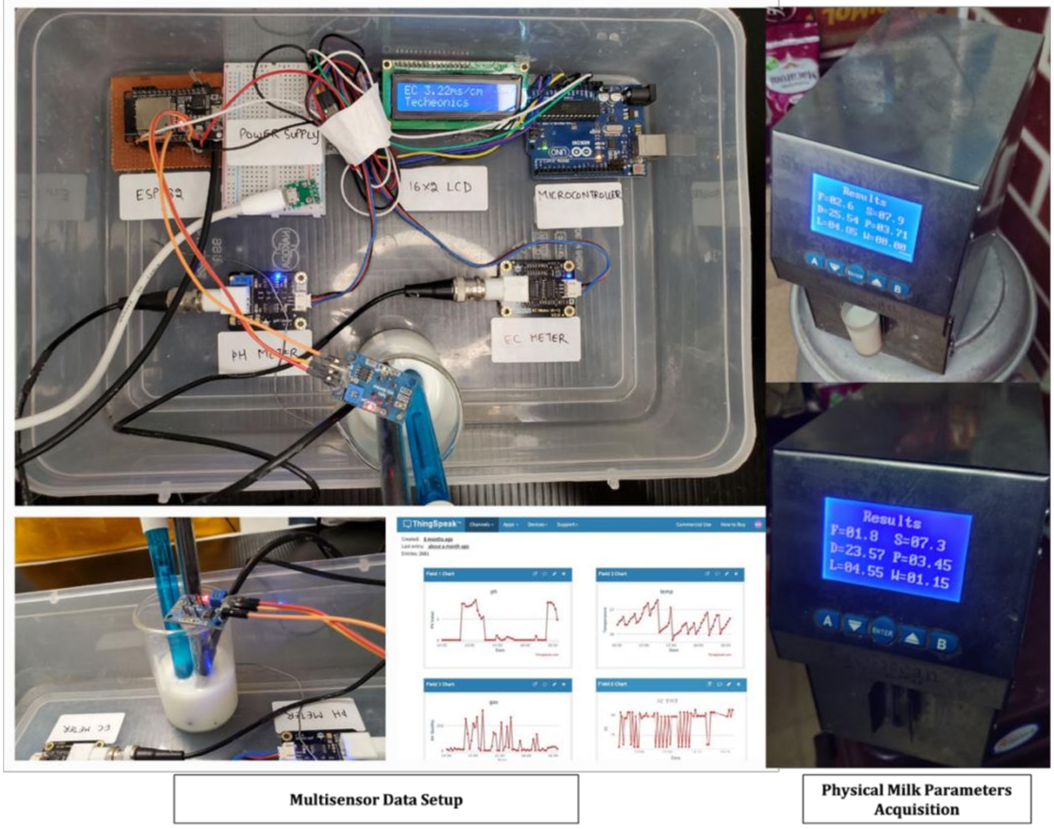
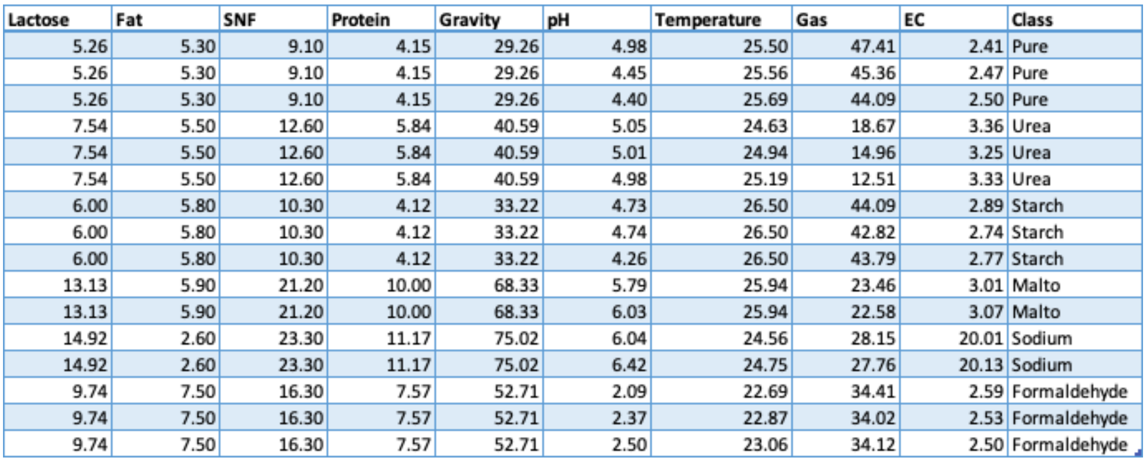


Figure 6.3 Milk Data Acquisition Setup

The data acquisition device is crafted by integrating IoT-based sensors and a microcontroller, depicted in Figure 6.3. This setup allows for live data streaming from the microcontroller to a cloud server, facilitating two-way data transfer. A sample of the acquired dataset is illustrated in Figure 6.4, providing a glimpse of the collected data.



Lactose	Fat	SNF	Protein	Gravity	pH	Temperature	Gas	EC	Class
5.26	5.30	9.10	4.15	29.26	4.98	25.50	47.41	2.41	Pure
5.26	5.30	9.10	4.15	29.26	4.45	25.56	45.36	2.47	Pure
5.26	5.30	9.10	4.15	29.26	4.40	25.69	44.09	2.50	Pure
7.54	5.50	12.60	5.84	40.59	5.05	24.63	18.67	3.36	Urea
7.54	5.50	12.60	5.84	40.59	5.01	24.94	14.96	3.25	Urea
7.54	5.50	12.60	5.84	40.59	4.98	25.19	12.51	3.33	Urea
6.00	5.80	10.30	4.12	33.22	4.73	26.50	44.09	2.89	Starch
6.00	5.80	10.30	4.12	33.22	4.74	26.50	42.82	2.74	Starch
6.00	5.80	10.30	4.12	33.22	4.26	26.50	43.79	2.77	Starch
13.13	5.90	21.20	10.00	68.33	5.79	25.94	23.46	3.01	Malto
13.13	5.90	21.20	10.00	68.33	6.03	25.94	22.58	3.07	Malto
14.92	2.60	23.30	11.17	75.02	6.04	24.56	28.15	20.01	Sodium
14.92	2.60	23.30	11.17	75.02	6.42	24.75	27.76	20.13	Sodium
9.74	7.50	16.30	7.57	52.71	2.09	22.69	34.41	2.59	Formaldehyde
9.74	7.50	16.30	7.57	52.71	2.37	22.87	34.02	2.53	Formaldehyde
9.74	7.50	16.30	7.57	52.71	2.50	23.06	34.12	2.50	Formaldehyde

Figure 6.4 Snapshot of the Acquired Milk Dataset

In this research, we utilized the t-test, a widely recognized statistical method, to investigate potential distinctions among various classes of milk samples based on their essential compositional parameters. Multiple classes of milk samples were collected for the study, and the relevant parameters were meticulously measured to evaluate potential adulteration. Before conducting the t-test, we rigorously assessed the fulfillment of test assumptions, including ensuring normality of data distributions and equality of variances. Upon analyzing the results, the t-test provided crucial insights into the statistical significance of differences between the classes. Table 6.2 presents the p-values for six classes obtained through the t-test.

Table 6.2. p -Values for different classes using t-Test

Sr. No	Class vs Class	Features having p-value less than 0.05	Mean Value
1.	Pure vs Urea (1 vs 2)	4 [pH, SNF, Lactose, Protein]	0.0021
2.	Pure vs Starch (1vs 3)	5 [Lactose, SNF, Protein, Gravity, EC]	0.00866
3.	Pure vs Malto (1 vs 4)	4 [Fat, Protein, Gravity, EC]	0.00034
4.	Pure vs Sodium (1 vs 5)	2 [Fat, pH]	0.0065
5.	Pure vs Formaldehyde (1 vs 6)	5 [pH, SNF, Lactose, Gravity, EC]	0.0048
6.	Urea vs Starch (2 vs 3)	1 [Protein]	0.0271
7.	Urea vs Malto (2 vs 4)	4 [Lactose, SNF, Protein, Gravity]	0.03125
8.	Urea vs Sodium (2 vs 5)	2 [Fat, pH]	0.00105
9.	Urea vs Formaldehyde (2 vs 6)	1 [Fat]	0.0013
10.	Starch vs Malto (3 vs 4)	1 [EC]	0.0477
11.	Starch vs Sodium (3 vs 5)	1 [pH]	0.0001
12.	Starch vs Formaldehyde (3 vs 6)	2 [Fat, Protein]	0.00735
13.	Malto vs Sodium (4 vs 5)	4 [Fat, pH, Lactose, SNF]	0.00124

14.	Malto vs Formaldehyde (4 vs 6)	5 [Lactose, Fat, SNF, Protein, Gravity]	0.00398
15.	Sodium vs Formaldehyde (5 vs 6)	4 [Lactose, Protein, Gravity, pH, EC]	0.0072
Weighted Mean			0.00708

Remarkably, the average p-value of 0.00708 lied below than 0.05 threshold mark. It allowed us to identify classes with statistically significant differences, demonstrating the effectiveness of the model on the dataset for adulteration detection purposes.

6.2.2 Sample Preparation

For the sample preparation, milk samples from commercial Murrah buffalo species were utilized for analysis [314]. These samples were collected from various milk centres in Dandrala Kharoud village, Patiala District, Punjab, India. Known concentrations of different adulterants, namely Urea, Starch, Sodium Bicarbonate, Maltodextrin, and Formaldehyde, were added to the milk samples during the experiment. The chosen adulteration ranges were based on typical circumstances encountered in practical scenarios [315]. The samples were processed to prepare the adulterated milk samples and obtain milk parameters and sensor readings, as outlined in Table 6.3. Initially, approximately 50ml of pure raw buffalo milk samples were taken in a glass beaker. The sensor probes were immersed in the milk to record corresponding readings. Pure milk samples and those mixed with adulterants were observed for a minimum of 10 minutes under ambient light. The multi-sensor system design facilitated the uploading of readings to the cloud every two minutes, resulting in five readings per sample.

A total of 50 milk samples were analyzed, leading to 250 instances for each class of pure milk, urea, starch, maltodextrin, sodium bicarbonate, and formaldehyde. The dataset contains 1500 observations in the CSV file, representing six milk sample classes (five adulterants and one pure class). The potential side effects of the various adulterants on human health are discussed in Table 6.3.

Table 6.3. Sample Collection for Various Adulterants and their harmful effects

Adulterant	**Concentration (w/v) per 50ml of pure milk**	**Health Effect**
Urea	5% (2.5gm)	It is added to milk to make up the density and nitrogen content, which boosts the protein level of milk. The functioning of the kidneys is seriously affected by urea [306].

Starch	10% (5gm)	It improves milk thickness and is added to adjust the consistency and viscosity of the milk. Starch consumption may result in diarrhoea in people [316].
Maltodextrin	15% (7.5gm)	It boosts the volume of milk and dairy products. Maltodextrin-adulterated milk consumption may result in allergies and diarrhoea [317].
Sodium Bicarbonate	10% (5gm)	The body's natural processes are disrupted by chronic excessive bicarbonate ingestion. Organs, including the liver and kidneys, may suffer harm [317].
Formaldehyde	10% (5gm)	It is added to increase the shelf life of the milk. It boosts the fat content of milk. It is believed to harm the liver and kidneys due to its high toxicity [3].

Figure 6.5 illustrates the sample preparation method for different types of adulterants used for the proposed milk adulteration detection system.

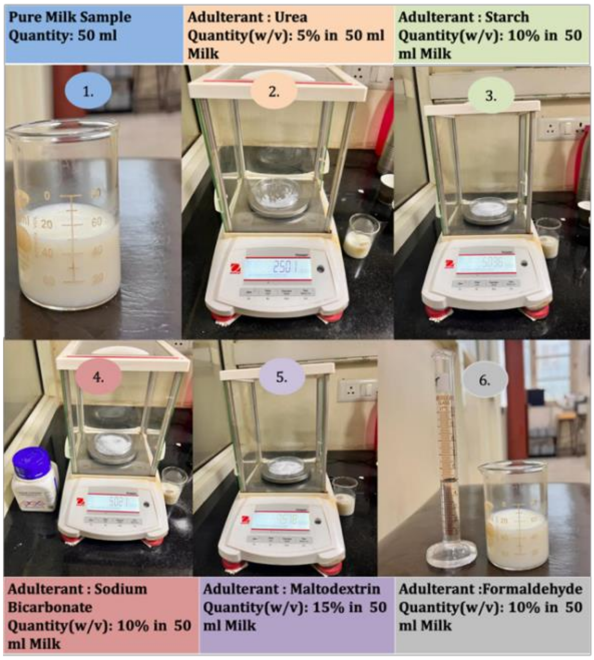


Figure 6.5 Sample Preparation for Milk Adulteration Detection

6.3 Implementation of the Milk Experiment

An ensemble approach based on machine learning is employed to classify and identify five distinct types of milk adulterants. The method combines multiple algorithms to achieve improved accuracy and reliability in detecting adulteration. By combining the predictions of several models, the ensemble approach can reduce the risk of misclassification and enhance the system's overall performance. The approach offers a promising solution to detect milk adulteration with high accuracy and efficiency, which can benefit the dairy industry and ensure the quality of milk products for consumers. This section explains various steps followed for the proposed milk adulteration detection system.

6.3.1 Preprocessing

The information gathered from sensors and the physical parameters has been structured in a manner suitable for analysis by a machine learning algorithm. The acquired data has been transformed using the min-max normalization method that rescales the values to maintain the range between 0 and 1. To handle multiple observations corresponding to each sample, these have been reduced to two observations using their mean and median values, respectively[308].

6.3.2 Proposed Ensemble Approach

An ensemble classifier is a machine learning model that combines the predictions of multiple individual classifiers to improve overall performance. Boosting is an example of ensemble learning, where a weak classifier is iteratively trained to achieve accurate classification and strengthened into a robust classifier. A weak classifier sub-model is produced during each iteration [318]. The following ML models are used for an ensemble approach to building a milk adulteration detection system.

- **Extra Tree:** Extra Trees is an ensemble machine learning algorithm that trains multiple decision trees and combines their results to make predictions. The algorithm aggregates the outputs of individual trees to obtain a final prediction. Extra Trees employs the complete dataset for training decision trees, and to promote dissimilarities between individual trees, it randomly chooses the feature split points to create child nodes.
- **Random Forest:** Random Forest is a well-known supervised learning algorithm utilized for classification and Regression problems in machine learning. The algorithm is based on ensemble learning, combining multiple classifiers to tackle complex problems and improve the model's performance. This method employs numerous decision trees generated on distinct subsets of the dataset. The resulting predictions are then averaged to enhance the accuracy of the model. Unlike a single decision tree, the random forest depends on the majority votes of predictions from each tree to predict the final output. A higher number of trees in the forest improves the model's accuracy and mitigates the risk of overfitting [319].
- **LightGBM:** LightGBM enhances the gradient boosting algorithm by incorporating an automatic feature selection technique and emphasizing the boosting of examples with more

significant gradients. LightGBM is a gradient-boosting framework that employs tree-based learning algorithms. It is known to be a highly effective algorithm in terms of computation and processing speed. Unlike other tree-based algorithms that grow horizontally, LightGBM grows vertically, following a leaf-wise approach instead of level-wise. This means it selects the leaf with the most significant loss to grow, enabling it to reduce more loss compared to a level-wise algorithm when extending the same leaf [311].

The real-time milk adulteration detection system focuses on identifying the adulterant present in milk with high efficiency and reliability. The three previously mentioned base classifiers (b_i) outputs the probability of each class, i.e., b_i(m)=($p_1, p_2, p_3, p_4 p_5, p_6$) for multi-classification task corresponding to 6 classes (Five adulterants and Pure Class). The output probabilities are weighted and averaged across each base classifier through a voting strategy. When the average probability of one class surpasses a certain threshold, the sample is classified as that adulterant-specific category. The final voting classifier is denoted as b as in Equations 6.1 and 6.2.

$$p(m) = \sum_{i=1}^{5} b_i(m) \tag{6.1}$$

$$b(m) = \begin{cases} Pure, p(p_1) \\ Urea, p(p_2) \\ Starch, p(p_3) \\ Maltodextrin, p(p_4) \\ Sodium\ Bicarbonate, p(p_5) \\ Formaldehyde, p(p_6) \end{cases} \tag{6.2}$$

6.3.3 Experimental Results

The computer system for conducting the experiments has an Intel core i9 processor operating at 1.20 GHz, 64 GB of RAM, and a 128-bit operating system. Python (version 3.9) with scikit-learn (version 1.1.1) library, among others, has been utilized to implement the data preprocessing algorithms and milk classification to identify various adulterants. To assess the effectiveness of the proposed system, a set of experiments is performed using 5-fold cross-validation to obtain the final outcomes. Several machine learning models have been experimented to develop an ensemble model for a milk adulteration detection system. The models studied in the literature [312], [313], [314] have been implemented on the acquired dataset to evaluate the performance of the models. Further, to check the robustness of the system, the ML algorithms have been used in fusion with the Ada-Boost method to get the comparative analysis of the various combinations of the models. The results of the different models to identify various adulterants in milk are discussed in Table 6.4.

Table 6.4. Comparative Analysis of Traditional ML Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
SVM (kernel: rbf, c: 0.1, gamma: 0.001)	52.54%	46.24	53.57	49.63
KNN	53.78	52.12	53.87	52.98
Decision Tree	79.65	79.32	79.58	79.44
Ada-Boost + Random Forest	78.23	77.16	78.34	77.98
Ada-Boost + Decision Tree	78.32	78.45	78.38	78.41
ANN	53.57	52.67	54.43	53.53
Extra Tree Classifier	81.03	81.89	80.34	81.10
Random Forest	81.02	81.42	79.96	80.68
Light GBM	82.04	82.74	81.03	81.87
Proposed Ensemble Approach	**96.00**	**96.33**	**95.33**	**95.50**

As observed from Table 6.3, the ML algorithms Extra Trees, Random Forest, and Light GBM have performed better than the other machine learning models, even when combined with two models for the milk adulteration detection system. Hence, these models have been considered for the development of an ensemble model. The hyperparameters for these models have been selected through a series of experiments. These experiments were designed to identify the combination of hyperparameters that would yield the best performance in terms of accuracy and generalization. A grid search method combined with cross-validation was employed to explore and evaluate various hyperparameter settings. The values of the hyperparameters are listed in Table 6.5.

Table 6.5. Hyperparameter Values for the ML Models

Model	Hyperparameters Values
Extra Trees	criterion=entropy, max_depth=8, max_features=6, min_samples_split=5
Random Forest Classifier	random_state=1, max_depth=10, max_features=5, min_samples_leaf=5, min_samples_split=7, n_estimators=300
Light GBM	random_state=1, max_depth= 10,learning_rate = 0.05, min_child_samples= 5, num_leaves = 10, reg_alpha = 0.03

It can be observed from Table 6.3 that the performance of the proposed model is highly convincing as compared to the individual machine learning classifiers in terms of all the evaluation metrics. The ROC curve class-wise and the average ROC Curve of the proposed model is shown in Figure 6.6.

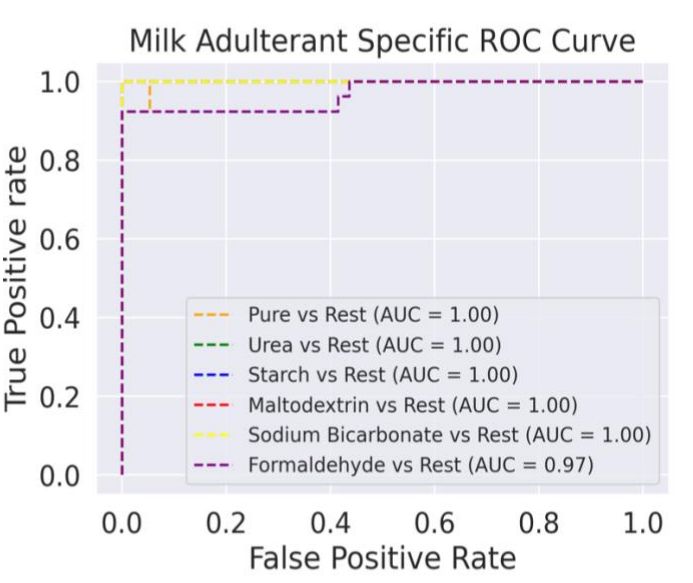


Figure 6.6a. Class-wise ROC Curve of the Proposed Milk Model

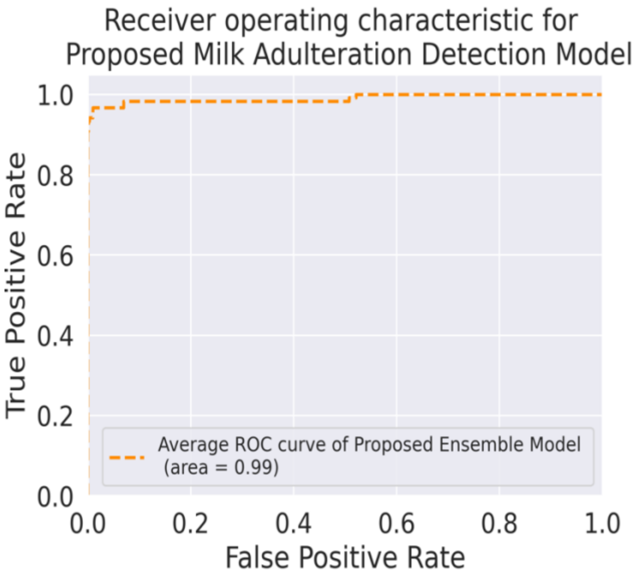


Figure 6.6b. Average ROC Curve of the Proposed Milk Model

The ROC curve represents the probability distribution of true positive rate (TPR) versus false positive rate (FPR) at various threshold levels. The AUC measures the overall performance of the ROC curve, with higher values indicating more accurate model predictions. In other words, the closer the AUC value is to 1, the better the model's predictive ability. As can be inferred in Figure 6.6b., the average AUC ROC Score value is 0.99 for the proposed model.

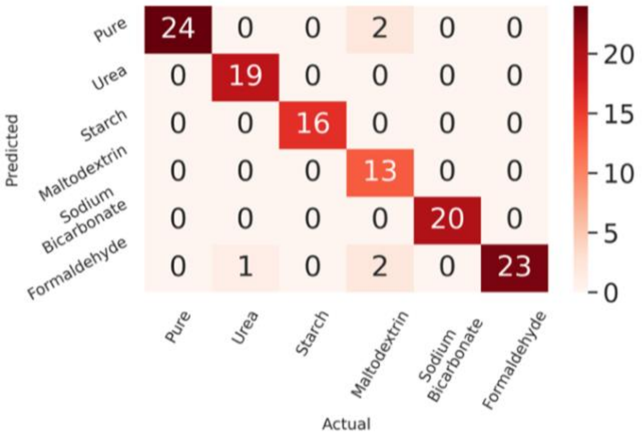


Figure 6.7. Confusion Matrix of the Proposed Milk Model

The Figure 6.7. displays the confusion matrix of the proposed model implemented in the proposed work for having a comparative analysis of various adulterants to know about the milk adulteration detection system.

6.4 Analysis of the Proposed Model

In this section, we present a comprehensive analysis of the proposed model for milk adulteration detection. The evaluation of the model involved multiple steps, including performance evaluation using various data splits, and k-fold cross-validation.

6.4.1 Analysis Using Multiple Data Splits

The acquired data has been split into multiple sets of training and testing to check the robustness and validate the model. The data has been tried and tested for 70%, 80% and 90% of training data, and 30%, 20% and 10% for testing data, respectively. The comparative analysis of the traditional algorithms Extra Trees, Random Forest, Light GBM, and the proposed models for 70%, 80%, and 90% data splits has been represented in Figure 6.8.

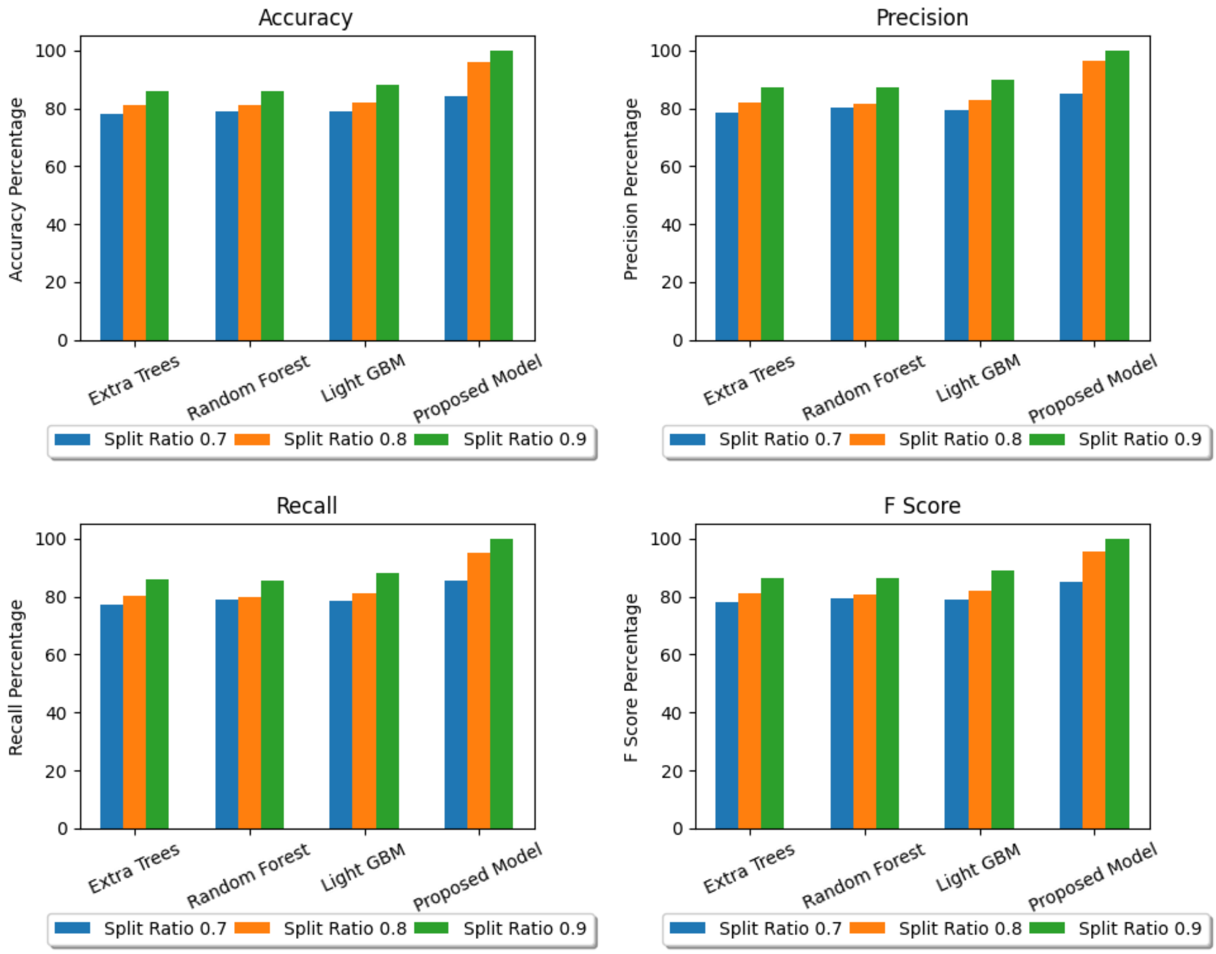


Figure 6.8. Comparative Analysis of the Proposed Milk Model and ML models for various Data split Ratio.

6.4.2 Analysis using k-fold Cross Validation

To validate the model's performance robustness, we employed 5-fold cross-validation. The dataset was divided into 5 subsets or folds, and the model was trained and tested 5 times, each time using a different fold as the validation set and the remaining folds as the training set. This process ensured that the model's performance was evaluated across multiple independent test sets, reducing the risk of overfitting and enhancing generalization. Notably, for every value of k the efficiency of the proposed model is consistent. The findings provide compelling evidence supporting the superior efficiency and robustness of the proposed model. The performance of the proposed model for different values of k is shown in Figure 6.9.

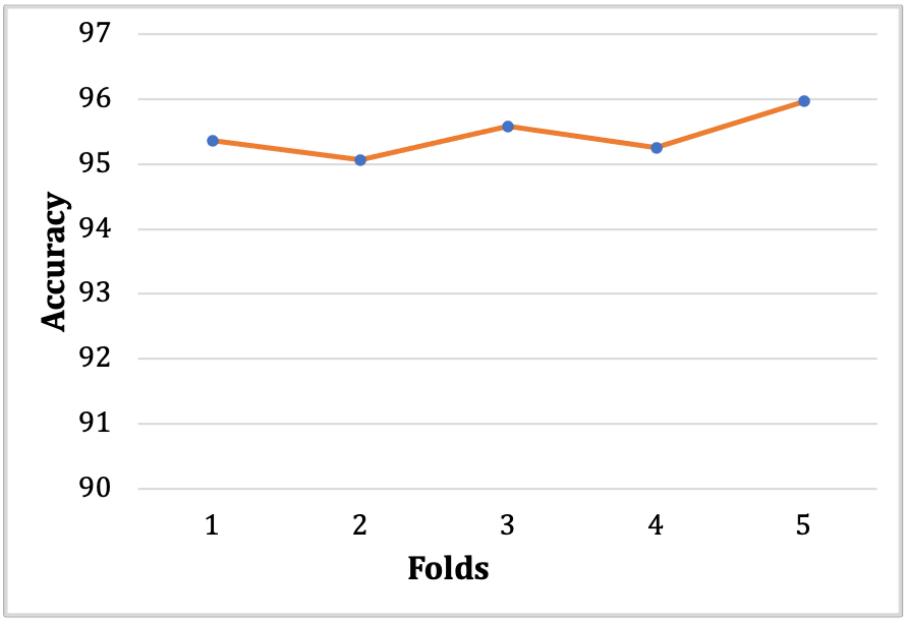


Figure 6.9. K-Fold Cross Validation for Accuracy

6.5 Employing XAI to Elucidate the Proposed Model for Milk Adulteration Detection

Explainable AI (XAI) comprises methods and techniques within artificial intelligence (AI) that strive to make AI solution outcomes understandable to humans. In contrast to the enigmatic "black box" of machine learning, where designers are often unable to elucidate AI's specific decisions, XAI potentially embodies the societal right to explanation. Its relevance transcends legal mandates; for instance, XAI can enhance user trust in AI-driven products or services, ensuring a positive user experience by fostering confidence in the AI's decision-making. XAI's overarching goal is to unveil the sequential nature of decision-making, encompassing past, present, and future actions while concurrently revealing the foundational information on which these actions are grounded. This multi-faceted trait empowers the affirmation, interrogation, and generation of knowledge, enabling validation, challenges to, and innovation of existing understandings [324].

Explainable AI (XAI) offers transparency by elucidating the model decisions in the realm of the proposed milk adulteration detection model. This transparency instills trust, aids in identifying adulteration factors, and strengthens quality control. XAI's interpretable insights empower stakeholders to comprehend the reasoning behind AI-based determinations, enhancing accountability and facilitating informed decision-making for ensuring milk quality and safety [325].

6.5.1 Analysis Using SHAP

SHAP (SHapley Additive exPlanations) is a widely adopted Explainable AI (XAI) framework that enhances the interpretability of machine learning models. Built on cooperative game theory principles, SHAP offers insights into how individual features influence model predictions. By quantifying the contribution of each feature to a prediction, SHAP values provide a clear understanding of the decision-making process. This is particularly valuable for complex models. The Shapley value for a specific feature in a prediction can be mathematically expressed as in Equation 6.3.

$$\emptyset_i(f) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|!\,(|N| - |S| - 1)!}{|N|!} [f(S \cup \{i\}) - f(S)] \tag{6.3}$$

Where:

- $\emptyset_i(f)$ is the Shapley value for feature i in the prediction function f.
- N is the set of all features.
- S is a subset of features excluding feature i.
- $|S|$ is the number of features in subset S.
- $|N|$ is the total number of features.
- $f(S \cup \{i\})$ is the prediction function's output when features in subset S are combined with feature i.
- $f(S)$ is the prediction function's output when only features in subset S are considered.

The Shapley value calculates the average marginal contribution of a feature across all possible subsets of features. It quantifies the difference in predictions when including feature i compared to excluding it, weighted by the number of ways each subset can occur. This value provides an interpretable measure of how much each feature impacts the prediction in the context of the overall feature interactions.

6.5.2 Global Explanations using SHAP

Global explanations using SHAP involve understanding the overall behaviour of a model across its entire dataset. This can be useful for gaining insights into how different features impact the model's predictions on a broad scale.

The proposed framework incorporates a comprehensive analysis using SHAP to evaluate the impact of diverse adulterants on the compositional parameters of milk samples. Each key parameter is carefully measured to assess the level of adulteration within each milk class. Employing SHAP as an interpretable machine learning technique, we gain insights into the individual contributions of these parameters to detecting milk adulteration. Figure 6.10. showcases the SHAP outputs for the six distinct classes: Pure, Urea, Starch, Maltodextrin, Sodium Bicarbonate, and Formaldehyde.

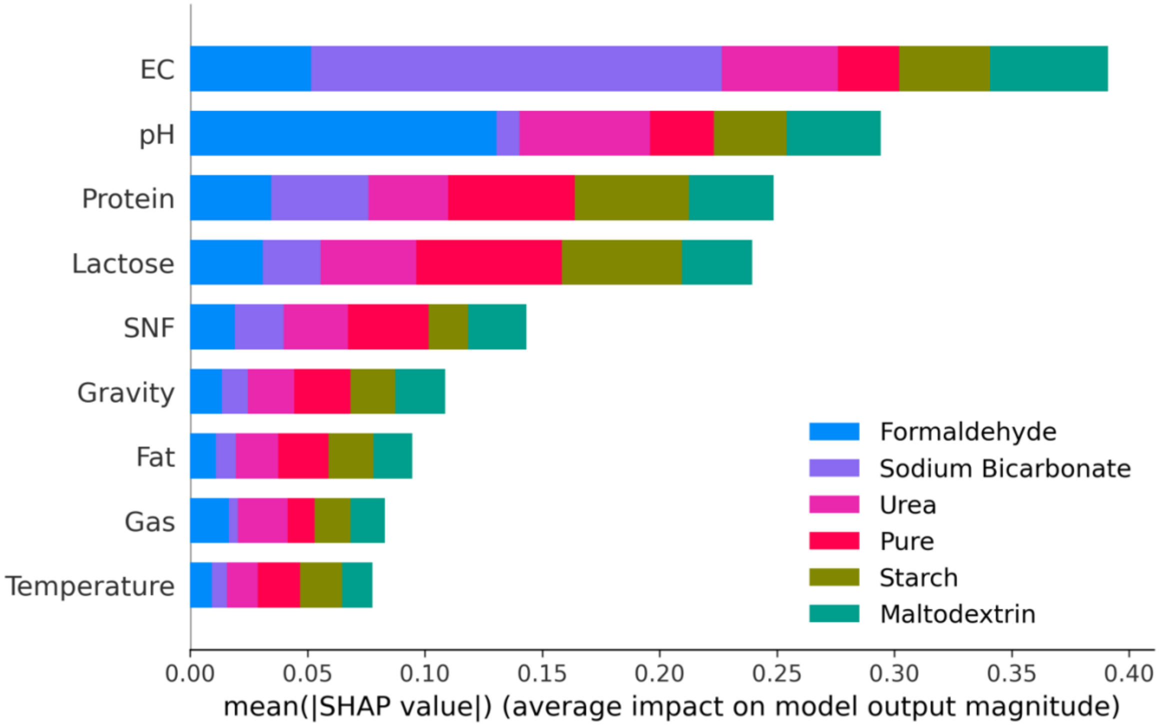
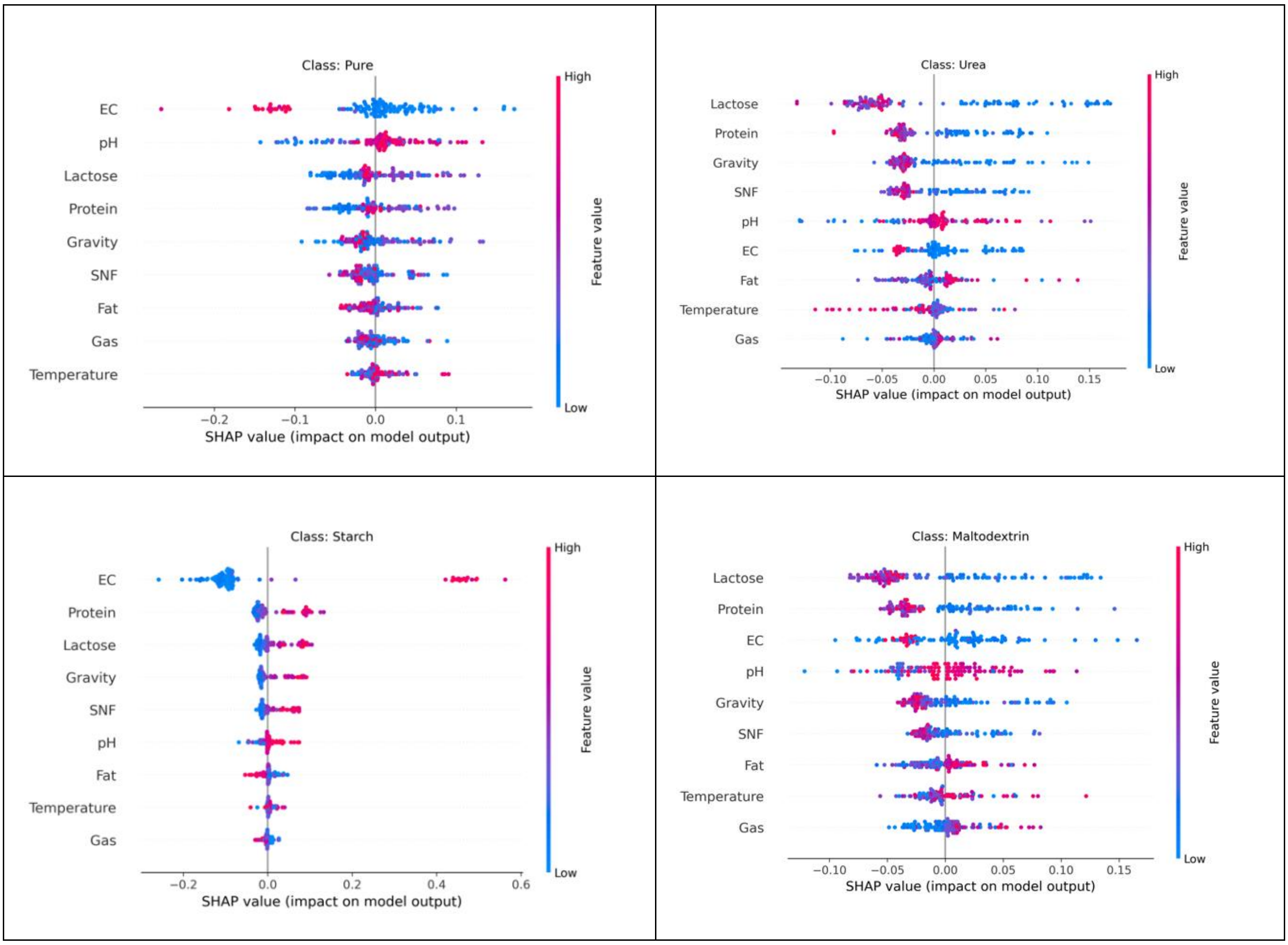


Figure 6.10 Global SHAP Analysis for Proposed Milk Adulteration Detection Model

By utilizing SHAP values, we successfully determined the primary influential features for each adulterant class, thus revealing insights into the fundamental mechanisms of adulteration detection. The EC and pH parameters emerged as the most crucial factors for milk adulteration detection. These findings strongly support the effectiveness of SHAP analysis in bolstering milk adulteration detection efforts and highlight its promising potential in safeguarding consumer safety and maintaining product integrity.

Global Explanations Class Wise

Class-wise explanations using SHAP involve understanding how different features contribute to the predictions of each class in the milk adulteration detection model. This approach can provide insights into the unique characteristics of each class and how different features influence the model's decisions for each class. The class-wise explanations are represented graphically in Figure 6.11. The SHAP summary plot components include Feature Importance, where the y-axis ranks features by their average absolute Shapley values per class, indicating higher-contributing features at the top; Feature Value, depicted by bars showcasing importance within value ranges along the x-axis; and Bar Color, representing positive/negative contributions through red/blue shades, with color intensity reflecting the contribution's magnitude. Consistently, features like EC, pH, Lactose, and Protein exhibit high importance across classes, while temperature and gas have lower influence. This visualization aids in how different features affect the model's decision-making for each class and potentially provides insights into the underlying patterns and relationships in the data.



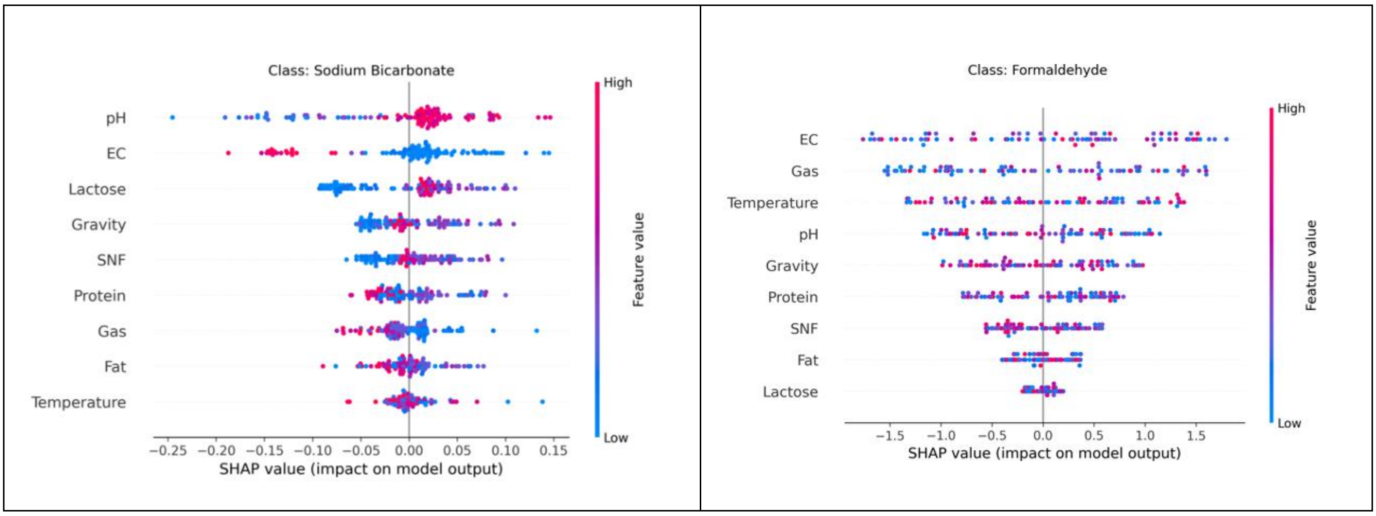


Figure 6.11 Class Wise SHAP Analysis for Proposed Milk Adulteration Detection Model

6.5.3 Local Instance Explanations

SHAP force plots are specific to individual instances, and the feature contributions may vary for different instances, depending on their feature values and how the model interacts with those values. Figure 6.12. illustrates the SHAP analysis for correctly predicted instances for each of the milk adulteration detection model classes. The generated graph using the SHAP force plot explains the model's prediction for a specific instance. The graph consists of two main components:

Feature Contributions: The graph displays the contribution of each feature to the model's output through horizontal bars, which can be either blue or red. A blue bar signifies a positive contribution of the feature's value to the model's prediction, while a red bar indicates a negative impact. The length of the bar represents the magnitude of the feature's influence on the prediction.

In the case of the "Pure" class, all features demonstrate a negative contribution to the prediction. However, for the "Urea" class, features like pH, Lactose, Gravity, and Fat positively contribute to the predicted outcome, whereas Temperature's impact is negative. For the "Starch" class, Gas and Fat exhibit positive correlations with the proposed model, whereas Gravity, SNF, Lactose, and Protein showcase negative correlations with the model's prediction. In the "Maltodextrin" class, Gravity, Fat, and pH display positive correlations with the proposed model, while Temperature, Lactose, and Protein exhibit negative correlations with the model's prediction. Regarding the "Sodium Bicarbonate" class, all features are positively correlated except pH. Conversely, within the "Formaldehyde" class, only EC negatively contributes to the model's prediction.

Base Value: The base value represents the expected model output when all features have a zero contribution. It serves as a reference point for interpreting feature contributions. For the proposed model, all the feature show some correlation towards the proposed model.

Figure 6.12. Local SHAP Analysis for Proposed Milk Adulteration Detection Model

6.6 Comparison of the Proposed work with the existing state-of-the-art methods

The literature shows that researchers have used ML, DL, and IoT-based spectroscopic methods to detect milk adulteration. The results of the proposed system have been compared to the existing state-of-the-art methods, as shown in Table 6.6.

Table 6.6. Comparison of the proposed milk model with the existing state-of-the-art methods

Author(s)	Results (%)
Ebrahimi et al.(2019) [317]	Accuracy: 84.90
Mu et al.(2020) [318]	Accuracy: 95.00
Fuyang et al.(2020) [312]	Accuracy: 94.60, Precision: 94.80, Recall: 87.00, F1-Score: 90.10

Farah et al.(2021) [92]	Accuracy: 88.50
Asefa et al.(2022) [319]	Accuracy: 94.00, Precision: 97.00
Proposed Model	Accuracy: 96.00, Precision: 96.33, Recall: 95.33, F1-Score: 95.50

It is evident from Table 6.5 that the results of the proposed system are comparable to the existing state-of-the-art methods. It integrates IoT with an ML-based ensemble approach to develop a real-time, economical, and robust system to identify various adulterants in milk. The developed model is easy to use and highly cost-effective milk adulteration detection system. The conclusion and future aspects are discussed in the next section.

Chapter Summary

The present study aims to develop a real-time, low-cost AI-enabled IoT milk adulteration detection system. The dataset is prepared by designing a data acquisition device using IoT-based sensors and a microcontroller. The real-time data is collected using sensors to test for pH, temperature, conductivity, and VOC. Also, the other physical parameters like Fat, Protein, SNF, Lactose, and Gravity values have been collected simultaneously for the milk samples in the proposed system. The proposed model is optimized using the Voting Ensemble Learning method to develop the milk adulteration detection system. In future studies, enlarging the dataset size can improve the model's generalizability. Additionally, a portable data acquisition system can be designed for the end user along with the mobile-based application.

Chapter 7

Conclusion and Future Scope

This thesis has focused on effectively exploring artificial intelligence techniques for detecting food quality. This concluding chapter encapsulates the research endeavours showcased throughout the thesis and sheds light on the prospective avenues for further investigation in this domain.

7.1 Conclusion

For the development of an efficient system for food quality detection using AI, this thesis offers a comprehensive exploration of existing terminologies, objectives, systems, and challenges in the field. Food quality is a critical factor influencing consumer satisfaction, public health, and the overall trustworthiness of the food supply chain.

Initially, the research delves into studies aligned with the objectives related to food quality detection. The thesis includes an extensive literature review encompassing existing research studies in AI-based food quality detection and adulteration. It thoroughly examines established methodologies for analyzing various food products, including quality statistics, analysis techniques, visualizations, and different AI algorithms for quality assessment. Additionally, the thesis investigates publicly available datasets, tools, and technologies crucial for conducting research within the domain of food quality detection using AI. The latest research studies and commonly used evaluation parameters are discussed, and research gaps have been identified.

However, it has been analysed that consistently and accurately assessing food quality, especially for perishable items like fruits and milk, presents several challenges. Conventional methods for quality detection are often time-consuming, labor-intensive, and subjective, which can lead to errors and inconsistencies. Artificial intelligence has emerged as a transformative technology with the potential to revolutionize various industries, including food quality assurance.

To bridge the gap of the conventional methods, the primary objective of this thesis is to present the development of an integrated system for food quality detection, with a specific focus on assessing the quality of fruits and milk using artificial intelligence. Fruits and dairy products are essential components of a balanced diet for most living beings, including humans, due to their nutritional content and health benefits as it contains necessary vitamins and minerals. The proposed system incorporates cutting-edge technologies and techniques, spanning data acquisition, image processing, and utilizing AI algorithms for quality evaluation. The system facilitates a comprehensive and efficient approach to food quality assessment by seamlessly integrating these components. Furthermore, the system can operate in real-time, enabling immediate decision-making regarding the acceptance or rejection of food products based on their quality. Additionally, the system is scalable, allowing for analysing large quantities of samples, thereby enhancing the overall efficiency of quality control processes.

Fruit quality evaluation is a multifaceted process that involves the comprehensive assessment of various attributes and characteristics to determine the overall quality of a fruit. Within the fruit sector, automated systems that facilitate fruit quality detection, especially amidst complex backgrounds, hold significant importance. The sorting of fruits significantly impacts the export market and quality evaluation. Notably, the appearance of fruits is a critical quality for grading, directly influencing their market value and consumer preferences. The system outlines a strategic approach for fruit quality detection to achieve precise fruit identification and comprehensive quality assessment through a two-tier system. The study majorly focused to collect the data for commonly used fruits which are apple, banana, orange and tomato. It leverages the YOLOv5 object detection system to create a specialized model. This intricate process involves meticulous dataset preparation, utilizing innovative mosaic data augmentation techniques supported by various noise removal filters and additional processing stages. The proposed system's effectiveness is evaluated through its predictive performance. After rigorous training on distinct dataset features, the model's ability to accurately predict labels for testing samples demonstrates its operational efficiency and suitability for real-world applications. The model can be further generalised by including plant based images in the dataset and explore the feasibility of incorporating environmental information as additional input features to the multi-object detection model to track the ripening process over time.

Additionally, most perishable fruit of the collected dataset tomato is further explored to evaluate shelf life of the fruit based on its ripeness index. The research introduces a dedicated tomato quality detection system, which focuses on analyzing specific attributes to ensure precision in quality evaluation. It has been a substantial contribution to the field of tomato quality assessment, bridging both manual and automated techniques for feature extraction. These features are pivotal in evaluating tomato quality in terms of ripeness and suitability, crucial factors impacting shelf life. It introduces an ensemble machine learning approach, using regression methods to predict these key parameters. The model's development begins with acquiring a meticulously curated image dataset from various market vendors, followed by rigorous data cleansing to ensure reliability. The model's training incorporates a blend of handcrafted and deep learning-generated features. Comparative analysis with existing models reinforces the remarkable effectiveness of our proposed methodology.

Further, the research explores dairy products besides fruits to evaluate milk quality. The milk quality evaluation is a vital process that entails a comprehensive assessment of various attributes and components to ascertain the overall quality and safety of milk. This evaluation is critical in the dairy industry, influencing consumer satisfaction, market demand, and public health. The system combines machine learning algorithms with data from IoT-based sensors for milk quality detection, continuously monitoring critical parameters such as pH levels, temperature, and fat content in real-time. A new dataset is prepared for various milk samples that combines the physical features along with the sensor based data. It unveils an innovative IoT-based multi-sensor system powered by artificial intelligence, specifically designed to detect milk adulteration, addressing the crucial need to safeguard milk's quality and safety. The system's uniqueness lies in integrating various sensors capable of real-time measurements, including pH, electrical conductivity (EC), temperature, gas parameters, and Volatile Organic Compounds (VOC) parameters. This comprehensive approach extends to quantifying essential milk constituents like Fat, Protein, Solids Not Fat (SNF), Lactose, and Gravity values. To identify specific adulterants such as Urea, Starch, Sodium Bicarbonate, Maltodextrin, and Formaldehyde, a machine learning-based ensemble technique is adroitly employed for effective classification. Integrating an IoT-based data acquisition device synchronized with the sensor system enhances measurement accuracy and efficiency. Furthermore, incorporating SHAP (SHapley Additive exPlanations) analysis provides valuable insights into the ensemble model's decision-making process. It represents a significant advancement in ensuring milk quality and safety through cutting-edge technology and data-driven approaches.

By integrating data from the fruit and milk quality detection modules, the system comprehensively assesses overall food quality. Combining artificial intelligence in food quality detection enhances consumer confidence and optimizes quality control processes, potentially leading to positive impacts on public health, sustainability, and overall customer satisfaction.

7.2 Future Work

The proposed AI-based food quality detection system holds immense potential to transform the food industry. It promises to revolutionize the food industry by ensuring safety, transparency, and sustainability in food production and distribution. These advancements will benefit producers and consumers, ultimately contributing to a healthier and more reliable food supply.

However, the present system can be extended further to enhance its utility and generalizability across the domain.

- For the Fruit Identification Quality Detection System, expanding its capabilities to recognize and evaluate a broader spectrum of fruits will ensure its relevance across the fruit industry. Utilizing the latest version of the YOLO model during training can enhance results significantly. Implementing this system at various stages of the fruit supply chain for continuous quality monitoring during transportation and storage is feasible. Integrating multiple sensors, including optical, chemical, and IoT-based, will offer a comprehensive perspective on fruit quality, yielding more comprehensive insights.
- In the context of tomato shelf life prediction, incorporating more advanced artificial intelligence and deep learning techniques will bolster data processing efficiency, leading to improved accuracy in detecting food adulteration and quality concerns.
- Leveraging IoT advancements to create precise sensors for real-time monitoring of milk quality parameters is advisable for Milk Quality Detection. Continuous refinement of machine learning algorithms can enhance the system's ability to identify and categorize milk adulterants accurately. Expanding the system's capability to detect specific quality parameters for various dairy products like cheese, yogurt, and butter is a valuable direction. Augmenting the dataset size can enhance the model's generalizability.

Food quality detection is rapidly evolving, driven by technological advancements and an increasing demand for safe, high-quality food products. The system architecture proposed in this research serves as a foundation for future innovations and enhancements in several key areas. The future of food quality detection in milk and fruits entails a convergence of cutting-edge technologies, emphasizing precision, transparency, and consumer empowerment. Continuous research, technological innovation, and industry collaboration will shape the landscape of food quality detection, ensuring the delivery of safe and high-quality products to consumers worldwide.

List of Publications

1. K. Goyal, P. Kumar, and K. Verma, "Food Adulteration Detection using Artificial Intelligence: A Systematic Review," ***Archives of Computational Methods in Engineering***, vol. 29, no. 1, pp. 397–426, Jan. 2022, doi: 10.1007/S11831-021-09600-Y/TABLES/15. (SCIE), IF-9.7
2. K. Goyal, P. Kumar, and K. Verma, "AI-based fruit identification and quality detection system," ***Multimedia Tools and Applications***, vol. 82, no. 16, pp. 24573–24604, Jul. 2023, doi: 10.1007/S11042-022-14188-X/FIGURES/22. (SCIE), IF-3
3. Goyal, K., Kumar, P. & Verma, K. "Tomato ripeness and shelf-life prediction system using machine learning", *Food Measure* **18**, 2715–2730 (2024). ***Food Measurement and Characterization***, https://doi.org/10.1007/s11694-023-02349-x, , (SCIE), IF-2.9
4. K. Goyal, P. Kumar, and K. Verma, "XAI-Empowered IoT Multi-Sensor System for Real-Time Milk Adulteration Detection," ***Food Control*** (2024)., https://doi.org/10.1016/j.foodcont.2024.110495, (SCIE), IF-5.6

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