Efficient Pre-Harvest Ripeness Estimation Techniques for Fruits

Thesis submitted in partial fulfillment of the requirements for the award of degree

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CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, "***Efficient Pre-Harvest Ripeness Estimation Techniques for Fruits***", in partial fulfillment of the requirements for the award of degree of Master of Engineering in *Computer Science and Engineering* submitted in Computer Science and Engineering Department of Thapar Institute of Engineering and Technology, Patiala, is an authentic record of my own work carried out under the supervision of *Dr. Sushma Jain and Dr. Avleen Malhi* and refers other researcher's work which are duly listed in the reference section.

The matter presented in the thesis has not been submitted for award of any other degree of this or any other University.

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

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ABSTRACT

The ripeness estimation of fruits plays an important role in marketing and evaluation of quality. However, due to the subjectivity, time consumption and slow speed in case of manual assessment, agriculture industry leads to the need of automation. In this research work, an efficient *ANFIS based Pre-harvest Ripeness Estimation (APRE) and Faster R-CNN based Ripeness Estimation (FRRE)* techniques have been proposed. In case of APRE, ripeness estimation of fruits is done based on colour. There are three main phases of the APRE: *Data Analysis* and *Processing, Input Feature Selection* and *Fuzzy Logic Controller deployment*. In the first phase, data set of images of fruits is prepared in image acquisition phase. Then images are pre-processed to make them equal in size. In Image Segmentation phase, a fruit is extracted from its background. The two colour features: red-green colour difference and red-green colour ratio are calculated on the basis of the extracted RGB colour attributes. The performance is analysed for these two colour features based on classification accuracy. Adaptive Neuro-Fuzzy Inference System (ANFIS) is utilized for designing and implementing the classification technique which will classify the fruits into four maturity stages. Training dataset is partitioned into four different classes which represent the four different stages of ripeness. In the second proposed technique i.e. FRRE, Faster R-CNN has been utilized. Region Proposal Network has been utilized in Faster R-CNN to generate the bounding boxes of probable regions where an object of interest can lie. This approach is also much quicker to deploy for new fruits, as it requires bounding box annotation rather than pixel-level annotation.

The performances of the proposed techniques are compared with three classification techniques: SVM, Decision Tree and KNN for the classification of the fruits on the basis of the ripeness in terms of specificity, F-Measure, precision, FP Rate, sensitivity and accuracy.

ABBREVIATIONS

Abbreviations	Full Form
ANFIS	Adaptive Neuro-Fuzzy Inference System
ANN	Artificial Neural Network
APRE	ANFIS based Pre-harvest Ripeness Estimation
CNN	Convolutional Neural Networks
FLC	Fuzzy Logic Controller
FN	False Negative
FP	False Positive
FRBCS	Fuzzy Rule Based Classification System
FRRE	Faster R-CNN based Ripeness Estimation
HOG	Histogram of Oriented Gradient
HSI	Hue Saturation Intensity
KNN	K-Nearest Neighbor
LBP	Local Binary Pattern
MF	Membership Functions
MFIS	Mamdani Fuzzy Inference System
NIR	Near-Infrared
NMS	Non-Maximum Suppression
PCA	Principal Component Analysis
PLS	Partial Least Square
RBPNN	Radial Basis Probabilistic Neural Network
R-CNN	Region-based Convolutional Neural Networks
RF	Random Forest
RGB	Red Green Blue
RPI	Ripening Index
RPN	Region Proposal Network
SURF	Speeded Up Robust Features
SVM	Support Vector Machine
TMI	Tomato Maturity Index

TN	True Negative
TP	True Positive
t-SNE	t-Distributed Stochastic Neighbour Embedding

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Chapter 1

INTRODUCTION

Images are considered as the most basic or appropriate method based on conception of human brain in physical classification of foodstuff in agricultural industry [1]. The factors which affect the fruits can be quantified visually, but this result in cumbersome and laborious process. The manual process is affected by physical factors which includes subjective results and inconsistent evaluation. The market prices are based on such inspections and the ‘‘best-if-used-before date”. The manual process followed by trained human investigators includes quality inspection by seeing and feeling. This method is significantly fickle, inconsistent and decisions are rarely similar among investigators. The analysis of fruits is a continual task for several aspect criterions in this type of environment; machine vision systems are best suited for quality assurance and conventional analysis. In agriculture, image processing and computer vision system are rapidly growing research areas which have significant analyzing techniques for pre to post harvesting of crops. Figure 1.1 shows the number of research growth in ripeness analysis. From this graph, the trend can be easily seen in this research field.

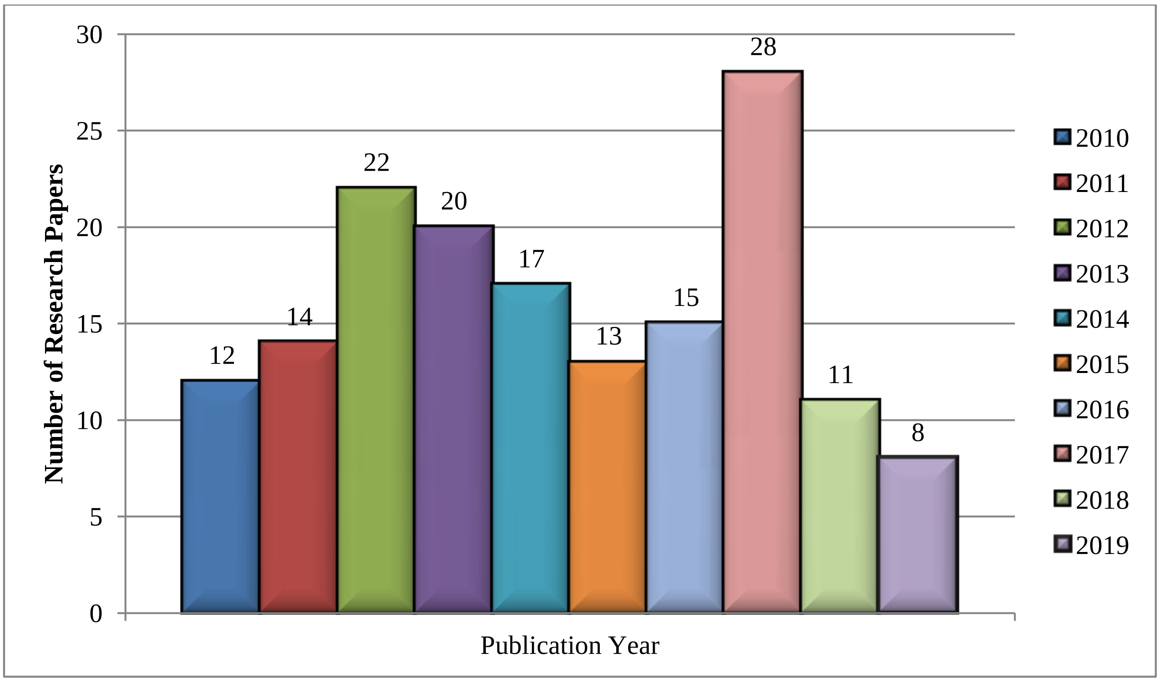

Figure 1.1: Research Growth in Ripeness Analysis

1.1 Ripeness Estimation

Harvesting of fruits at an appropriate maturity stage is the most significant step for achieving desirable quality[2]. The maturity level helps in selection of storage methods, estimation of shelf life and selection of processing operations for value addition. The maturity can be classified into two categories i.e. *horticultural maturity and physiological maturity*. Pre-harvest or Horticultural maturity is the development phase when a crop is suitable for harvesting. Post-Harvest or Physiological maturity stage is when a crop is capable of further ripening after it has been harvested i.e. suitable for processing or eating. Quality characteristics such as texture, color and flavor, [3] are maintained if the fruits are harvested at an optimal maturity phase. Hence, ripeness controlling and monitoring has become a significant issue in food industry.

Quality of the crop plays a significant role in consistent marketing. Ripeness is considered as the main quality indicator. The retailer or customer predicts the quality of fruits from the external or visual appearance. The ripeness is estimated by external appearance of the crop via various parameters such as size, colour and shape. The most important parameter of the crop is its colour as it has the highest impact on quality of the crop and preference of the customer. Certain colours are considered as preferable and results in better selling rates or prices in most of the cases of fruits. Colour is considered as the most important and highly utilized feature to determine the maturity stage for various fruits like watermelons, bananas, tomatoes, pomegranate[4] and dates etc.

Till now, optimal harvest date and period of storage of fruits is estimated manually by human graders by examining the visual appearance of the fruit based on a classification chart and practical experience. However, subjectivity is the main issue in manual estimation of ripeness. Tiredness can also be one factor which can hamper the effectiveness and accuracy. It is a cumbersome and time-consuming task in case of big greenhouses and farms. Fruits' ripeness estimation is an important process that affects its marketing and quality evaluation. However, time consumption, subjectivity and slow speed associated with manual assessment have been forcing the agriculture industry to apply automation. Hence, the automation process of ripeness estimation will result in a big advantage for agriculture industry and will minimize the inconsistencies in manual estimation of ripeness. The research work on fruits harvesting is carried out more than 20 years ago but still these reported works have not been used practically[2-9]. But with the advent of data storage and acquisition techniques, the work in this area especially harvesting techniques has gain a lot of attention again and is considered as an emerging research area among researchers [14–17]. The latest innovations are leading towards fulfilment of the demand for innovative methodologies in agriculture industry without any interference in natural growth of the crop [15].The goal of the study is to propose a machine vision based technique which can recognize the different ripeness stages of fruits. The vision system of harvesting is responsible for two-tasks. The first task is the detection or recognition of fruit and the second is the classification of recognized fruits.

1.2 Fuzzy Rule Based Classification System

Fuzzy Rule Based Classification System (FRBCS)[5][6] is considered as one of the most pervasive approaches which have been used in pattern classification problems due to its feature of interpretability.

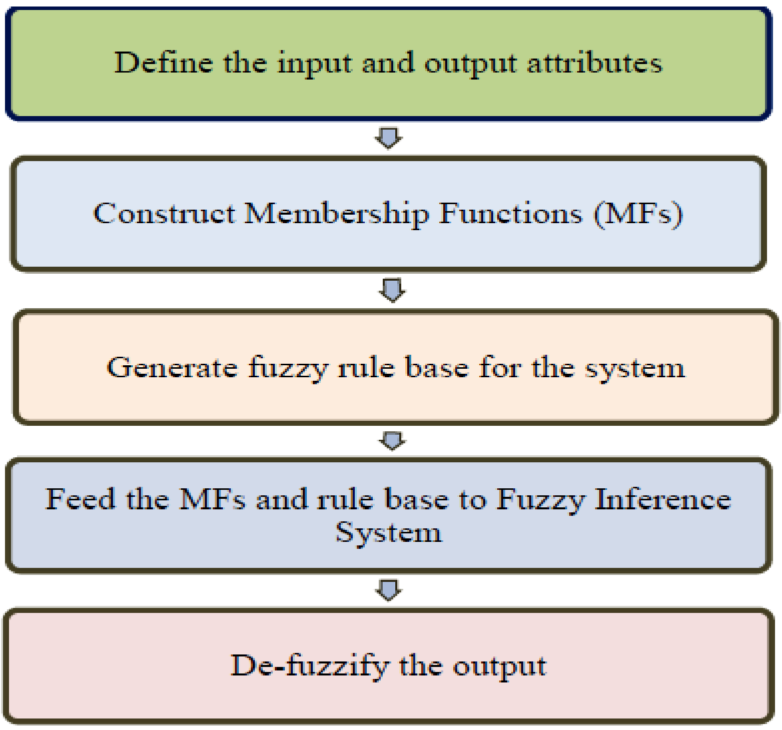

Figure 1.2: Workflow of Fuzzy Classification System

FRBCS has been utilized recently in classification problems such as geographical systems, medical applications and cancer classification etc. Fuzzy logic can transform the expert knowledge into the computer program quickly in form of if-then-rules. Moreover, the search space is reduced by expert knowledge while optimizing the system. The process of designing a FRBCS is shown in Figure 1.2.

1.3 Adaptive Neuro Fuzzy Inference System (ANFIS)

The ripeness of a fruit is basically fuzzy in nature. The colour changes from green to pink to the tones of red gradually. So, there is lack of crisp/threshold value based on which the ripeness stage of a fruit can be determined. Hence, the nature of the problem can be interpreted and solved by utilizing the concepts of fuzzy logic. Adaptive Neuro Fuzzy Inference System **(**ANFIS)[7][8] tunes membership function parameters of Sugeno-type fuzzy inference systems. It generates an initial structure of inference system automatically based on the training data. It modifies the inference system structure before tuning. It prevents over-fitting to the training data using additional checking data. It tests the generalization ability of the tuned system using testing data. The ANFIS model extracts linguistic rules from the expertise of experts, but also provides the optimization of models based on input and output data as compared to the existing fuzzy reasoning system.

The membership function is adjusted in such a way so that the model fits the given data and is efficient for the modeling of non-linear objects [9][10]. In ANFIS model, a learning mechanism is provided by neural networks to make a decision and to choose fuzzification component models and evaluate the inaccuracies or uncertainties of the decision parameters and behavior. It is a hybrid approach based on fuzzy inference system and a neural network. It incorporates the self-organizing learning. The knowledge base of the ANFIS model comprises two components: a database and a rule base. The rule base comprises "if-then" fuzzy rules. The database consists of the Membership Functions (MFs) of the fuzzy sets in the fuzzy rules. The membership function can be tuned based on the generated rule base gradually. Thus, the fuzzy reasoning system is more consistent with the actual input and output situation. The input variables of the fuzzy reasoning system are fuzzified first and then the fuzzy output variables are extracted from the decision logic unit. De-fuzzification module generates the final output.

The data set is divided into two equal parts in ANFIS as: training and testing data [24]. A training phase is an iterative process to calculate optimized values of parameters of the system by minimizing the sum of squared differences between training and model predictions data values. Initially, there is a need to fuzzify the input parameters by utilizing an appropriate partitioning technique. In this research work, sub-clustering technique is utilized to fuzzify the input variables. In the second step, the first-order Sugeno FIS with linear output function is selected as the inference system. Later, ANFIS structure is completed by the selection of hybrid learning algorithm. Then fuzzy rules are established for the inference system. In the rule-base, fuzzy variables are connected with fuzzy AND operators and rules are associated using max-min decomposition technique. Hence, training process is executed for epochs and process is terminated when there is stability in error decrement.

Consider a fuzzy reasoning system with two inputs x, y and an output f. For a first-order fuzzy model inference system of the Sugeno type consisting of n rules, if the i^{th} rule is defined as Rule i, then,

$$Rule\ i: if\ x\ is\ A_i\ and\ y\ is\ B_i\ then\ f_i = p_i x + q_i y + r_i \tag{1.1}$$

where x and y are input variables and A_i and B_i are linguistic variables. Here, p_i, q_i and r_i in the i^{th} rule are determined by the measured data and these values reflect the inherent characteristics of the system. As shown in Figure 1.3, the set of "if-then" rules represents the reasoning mechanism of the Sugeno fuzzy model, whereas w_i represents the firing strength of the i^{th} rule. This model has two components as specified: a premise and consequent part. In the Sugeno fuzzy model, the parameters of the model output function are unknown. To implement the Fuzzy Logic Controller (FLC) model, these parameters must be determined by ANFIS and the structure is presented in Figure 1.4. This method can realize the mapping process from the given input to the output using fuzzy logic to achieve feeding decision-making control. In Figure 1.4, the same layer of network nodes has the same function type. The model consists of 5 layers, in which each output signal from the upper layer is the input to the nodes of the next layer.

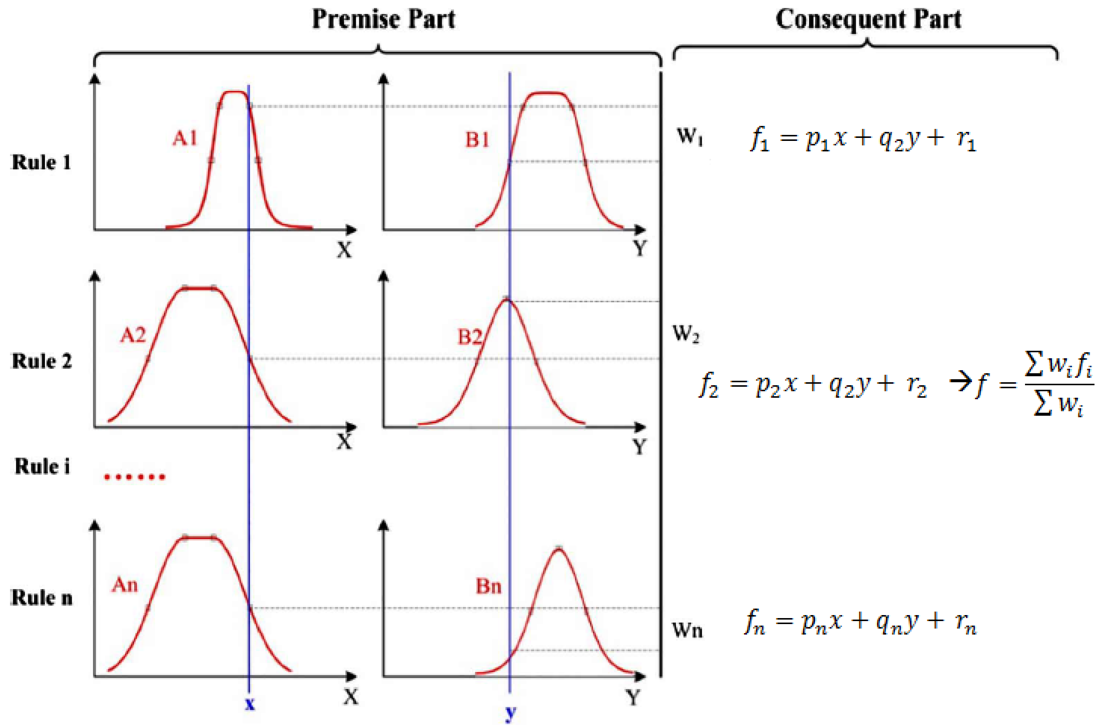

Figure 1.3: Reasoning Mechanism of Sugeno Fuzzy Model

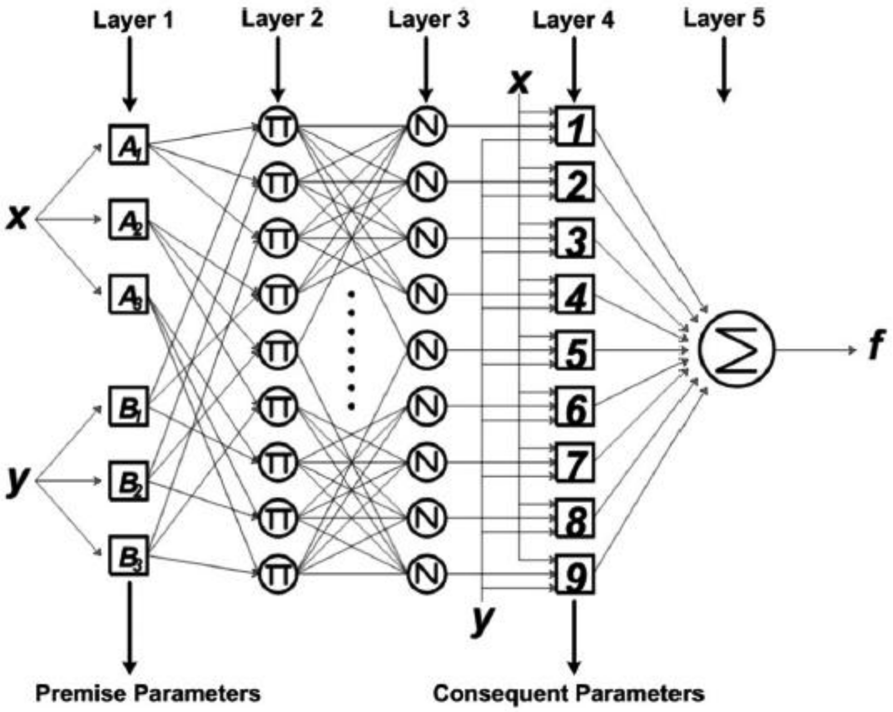

Figure 1.4: Two-input First-Order Sugeno Fuzzy Model

Layer 1: Input layer

Adaptive nodes are considered in the phase. The input variables are mapped to the fuzzy set and the membership is calculated. The bell-shaped membership function is used, which is calculated as given by Equation (1.2):

$$O_i^1 = \mu_{Ai}(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2bi}} \tag{1.2}$$

where O_i^j represents the i^{th} node of layer l, x is the input to node i, and A_i is the linguistic label associated with this node function. Here, $\{a_i, b_i, c_i\}$ are the parameters that change the shape of the membership function, which are called the premise parameter.

Layer 2: Rule layer

Fixed nodes are considered in this layer. The precondition of fuzzy rules between variables is matched and the weight value or firing strength w_i of each rule is computed, based on Equation (1.3):

$$O_i^2 = w_i = \mu_{Ai}(x).\mu_{Bi} \tag{1.3}$$

Layer 3: Weighted average

Every node in this layer is a circle node labeled N as shown in Figure 1.4.Tthe ratio of the i^{th} rule's firing strength to the sum of all rules' firing strengths is calculated for the i^{th} node. The output of this layer is called the normalized firing strength.

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + \ w_2 + w_3} \tag{1.4}$$

Layer 4: Inference layer

The main task of this layer is to calculate the contribution of each rule in the final output and the node function is defined as follows:

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \tag{1.5}$$

where $\{p_i, q_i, r_i\}$ are the consequent parameters of the fuzzy inference.

Layer 5: Output layer

This layer calculates the overall output as the summation of all incoming signals, the node function is as follows:

$$O_i^5 = \sum \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{1.6}$$

Through hybrid learning, ANFIS can model, analyze and simulate the mapping relationship between output and input data. Thus, the optimal distribution of membership function can be calculated. ANFIS utilizes least squares and gradient descent to adjust the parameters of input and results in high convergence speed. Each step is divided into a backward pass and forward pass of the hybrid learning algorithm and during which parameter adjustment and signal transfer are completed. In the forward pass, the function signal and the input data are transmitted forward. When the signal is transmitted to the fourth layer, consequent parameters are adjusted by the least square method. In the backward pass, the error signal is transmitted to the -input node from the system output node in the reverse direction. The gradient descent method is utilized to tune the premise parameters. In this work, the input is Red Green difference parameter and the output is the ripeness stage decision.

1.4 Faster R-CNN

Deep learning is a novice technique that includes more than one layer between input and output in which output from the previous layer is taken as input in every successive layer[11]. Deep learning has the ability to learn intermediate concepts between raw input and target which would produce far better understanding of the image data. It extracts features from the data on its own without any need of human intervention. The ability of deep learning to learn from unlabeled data with good accuracy is what makes it different from the previous algorithms available in machine learning. Convolutional Neural Networks (CNN) is a very popular algorithm for image classification and typically comprises of convolution layers, activation function layers and pooling layers to reduce dimensionality without losing a lot of features. There is a feature map that is generated by the last layer of convolutional layer. For example, if a cat image or a dog image is provided as input, the algorithm can tell whether it is dog or cat. Many pre-trained models are developed to directly use them without going through the lengthy process of training models due to computational limitation. There are various models available such as VGG-16, ResNet 50, DeepNet and AlexNet by ImageNet etc. To generate these so called "proposals" for the region where the object lies, a small network is slide over a convolutional feature map that is the output by the last convolutional layer.

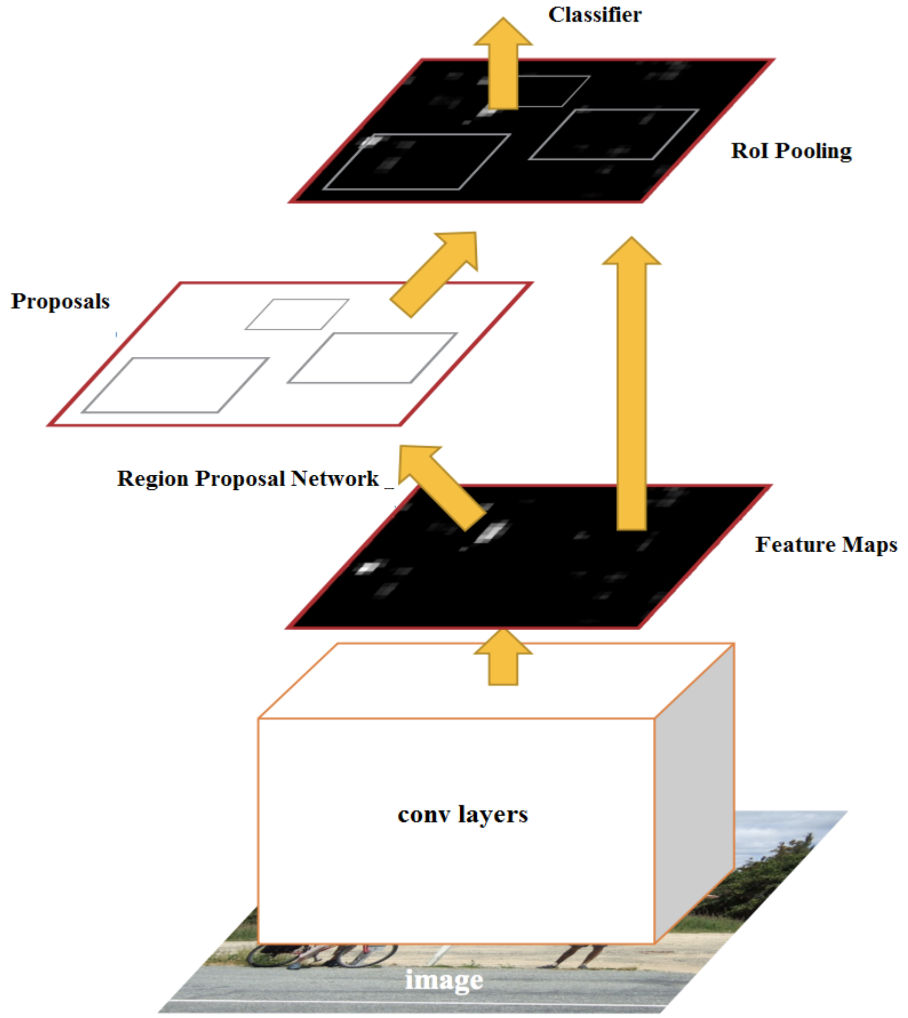

Figure 1.5: Faster R-CNN Architecture

Faster R-CNN[12] [13] comprises two networks: First one is Region Proposal Network (RPN) which is used to create region proposals and second one is a network which uses these proposals to detect objects as shown in Figure 1.5. The time cost of generating region proposals is much smaller in RPN than selective search, when RPN shares the most computation with the object detection network. The anchors or region boxes are ranked by RPN and the region having higher chances of objects is proposed. The workflow of Faster- CNN is depicted in Figure 1.6.

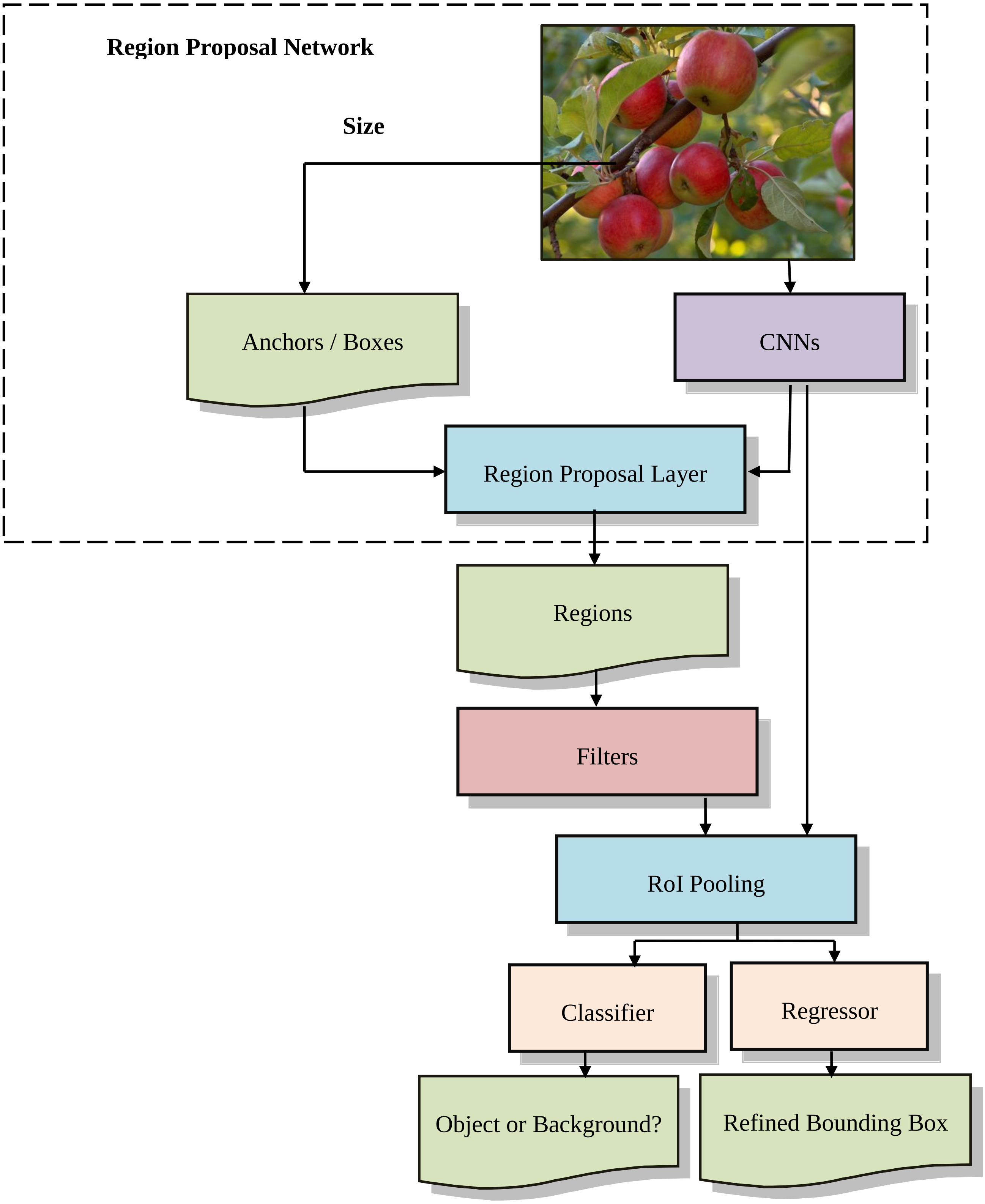

Figure 1.6: Workflow of Faster R-CNN

An anchor is a box which plays a significant role in Faster R-CNN. There are 9 anchors at a position of an image in the default configuration of Faster R-CNN. Figure 1.7 shows 9 anchors at the position (320, 320) of an image with size (600, 800). These anchors are assigned label based on two factors: First, the anchors with highest intersection-over-union overlap with a ground truth box are selected. The anchors with Intersection-Over-Union Overlap higher than 0.7 are chosen.

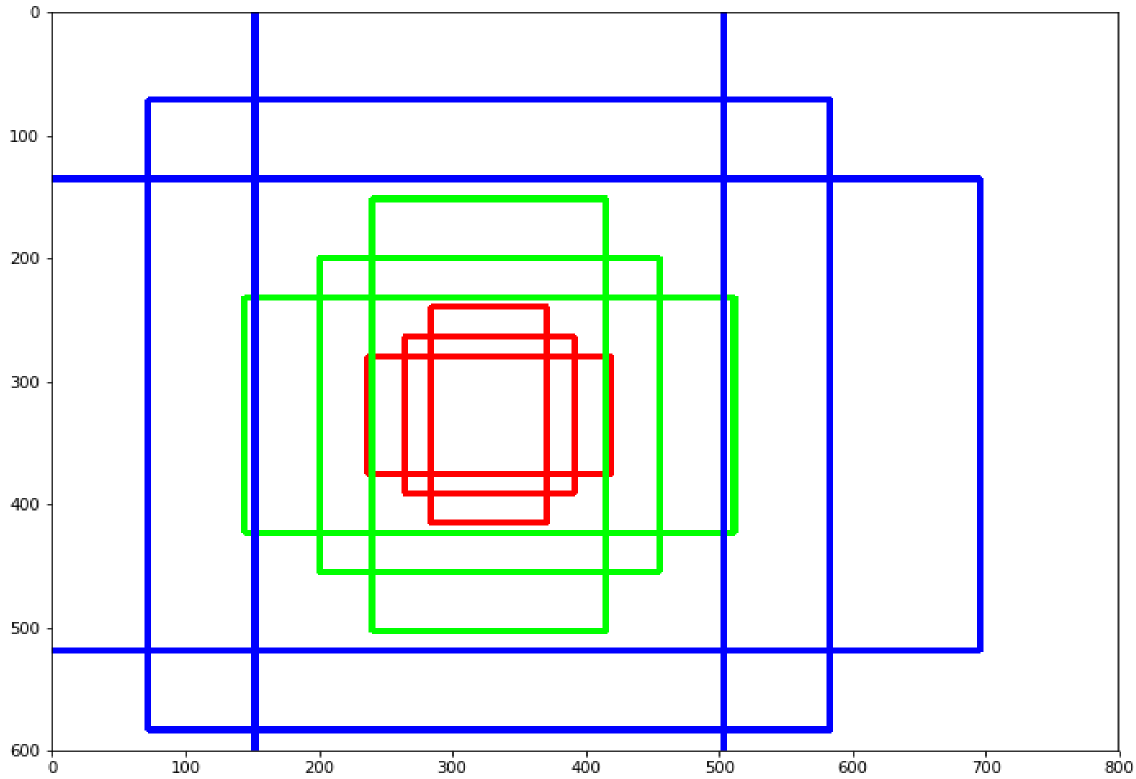

Figure 1.7: Anchors of an Input Image

1.4.1 Region Proposal Network

The RPN generates a bunch of proposals which will be checked by a classifier and regressor to check the occurrence of desired object eventually. The probability of an anchor being foreground or background is predicted by RPN and also the anchor is refined as shown in Figure 1.8. The RPN module serves as the ‘attention’ of this unified network as shown in Figure 1.9. The proposal is generated for the objects by RPN. It has a unique and specialized architecture in itself. RPN has a regressor and classifier. Anchor is the central point of the sliding window. For ZF Model which is an extension of AlexNet, the dimensions are 256-d and for VGG-16, it is 512-d. Classifier determines the probability of a proposal having the target object. Regression regresses the coordinates of the proposals.

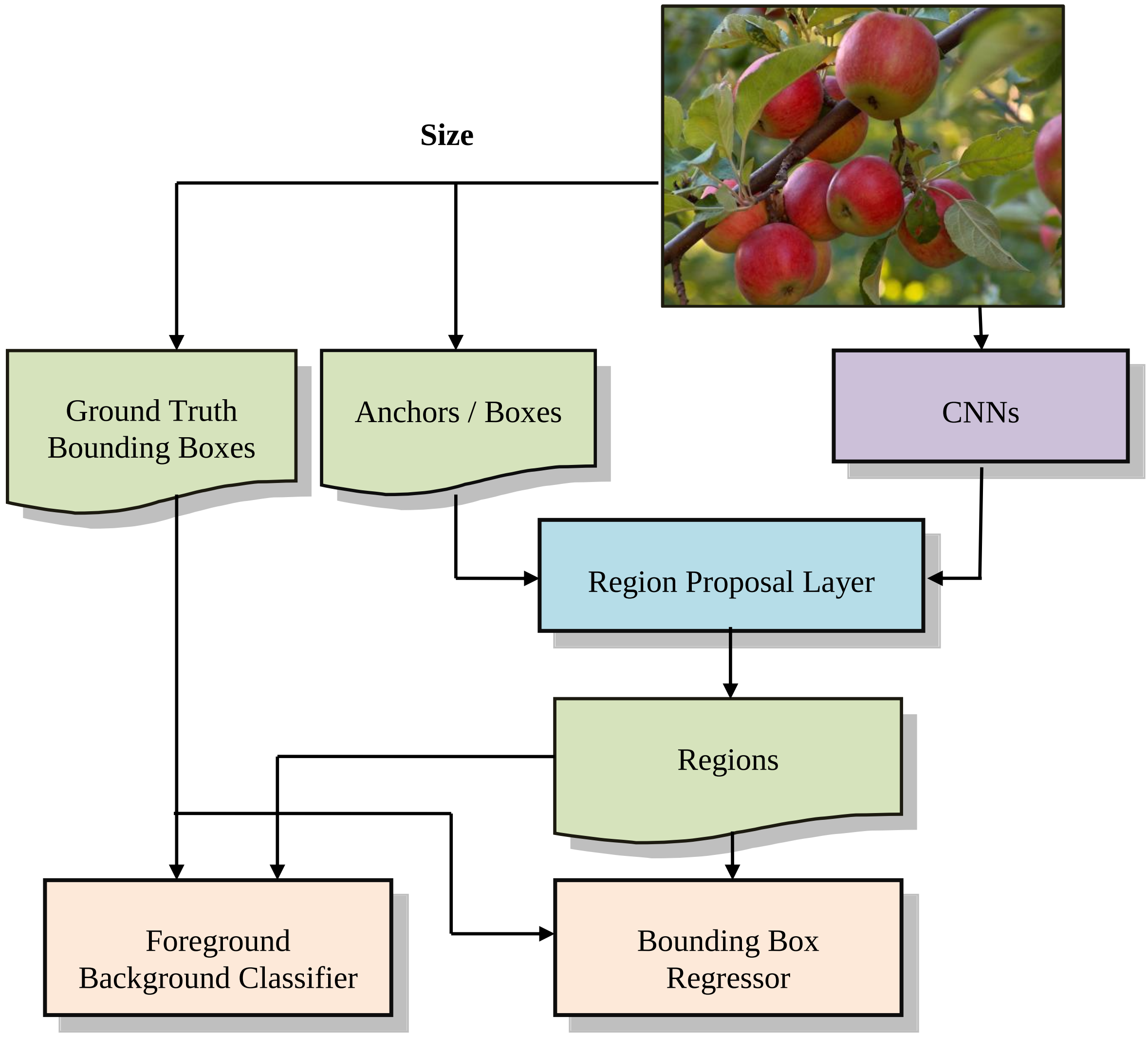

Figure 1.8: Workflow of Region Proposal Network

For any image, scale and aspect-ratio are two important parameters. The developers chose 3 scale and 3 aspect-ratio. So, total of 9 proposals are possible for each pixel, and the value of K is decided, $K = 9$ for this case. For the whole image, number of anchors is $W * H * K$. This is less time consuming and more cost efficient than previously proposed algorithms like Multi-Box. RPN is an algorithm that needs to be trained. So, Loss Function has been defined as follows:

$$L(\{p_i\}\{t_i\}) = \left(\frac{1}{N_{cls}}\right) \times \sum L_{cls}(p_i, p_i^*) + (\lambda/N_{reg}) \times \sum p_i * L_{reg}(t_i, t_i^*) \tag{1.7}$$

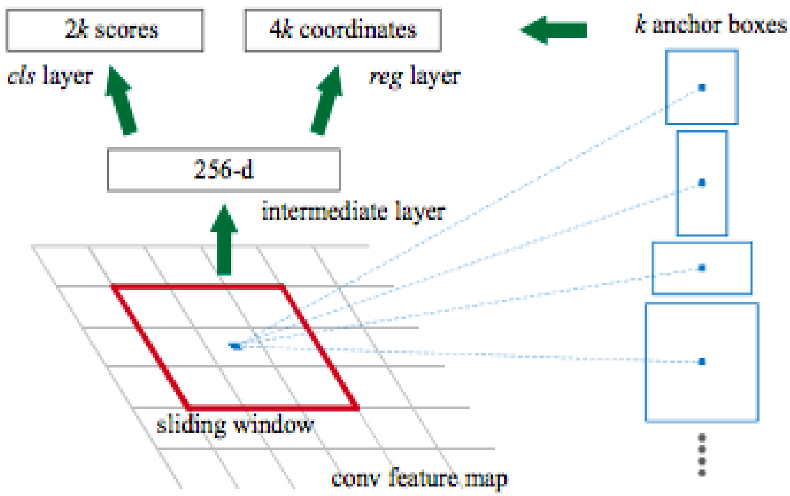

Figure 1.9: Base Architecture of RPN

i → Index of anchor, p → probability of being an object or not, t →vector of 4 parameterized coordinates of predicted bounding box, $*$ represents ground truth box. L for cls represents Log Loss over two classes.

$$L_{reg}(t_i, t_i^*) = R(t_i - t_i^*) \tag{1.8}$$

p^* with regression term in the loss function ensures that if and only if object is identified as yes, then only regression will count, otherwise p^* will be zero, so the regression term will become zero in the loss function. N_{cls} and N_{reg} are the normalization factors. Default λ is 10 by default and is done to scale classifier and regressor on the same level. Different kinds of anchors can be designed based on the object which needs to detect. A well designed set of anchors results in good accuracy and speed.

The first step of training a classifier is to make a training dataset. The training data is the anchors which are generated from the above process and the ground-truth boxes. The problem which is needed to be solved here is how the ground-truth boxes can be used to label the anchors. The anchors having the higher overlaps with ground-truth boxes are labeled as foreground, the ones with lower overlaps are labeled as background. Apparently, it needs some compromise and tweaks to separate background and foreground.

Let's say the 600×800 image shinks 16 times to a 39×51 feature map after applying CNNs. Every position in the feature map has 9 anchors and every anchor has two possible labels: foreground or background. If the depth of the feature map is defined as as 18 (2 labels X 9 anchors), then every anchor has a vector with two values (normal called logit) representing background and foreground. If logit is provided as input into a softmax/logistic regression activation function, the labels will be predicted. Now the training data is complete with features and labels. If the process of labeling anchors has been followed, then the anchors can be picked out based on the similar criteria for the regressor to refine. Anchors labelled as background should not be included in the regression, as ground-truth boxes are not available for these anchors.

After RPN, proposed regions are generated with different sizes. Different sized regions result in different sized CNN feature maps. It is difficult to generate an efficient structure to work on features with different sizes. Region of Interest Pooling reduces the feature maps into similar size. Unlike Max-Pooling which has a fix size, the input feature map is divided into a fixed number of roughly equal regions in ROI Pooling and then Max-Pooling is applied on every region. The output of ROI Pooling is same irrespective of the size of input. With the fixed ROI Pooling outputs as inputs, a lot of choices for the architecture of the final classifier and regressor are available.

1.5 Structure of Thesis

The structure of the thesis is as follows.

- **Chapter 2:** This chapter includes the literature survey of the presented work and the different techniques used for ripeness classification. It helps to analyze the gaps in previous work done.
- **Chapter 3:** This chapter lists the gaps in previous work, explains the problem statement and the main objectives of the thesis.
- **Chapter 4:** Based on the problem statement, the chapter deals with the approach followed to solve the problem and meet the objectives. It provides the detailed workflow model and various techniques applied for pre-harvest ripeness classification.
- **Chapter 5:** This chapter demonstrates the implementation results of the different techniques used for pre-harvest ripeness classification. The results

are then analyzed to find out the better technique for pre-harvest ripeness classification.

- **Chapter 6:** Finally this chapter provides the conclusion drawn from the results obtained and the summary of contributions made through this thesis. It also explains the future scope of the proposed work.

Chapter 2

LITERATURE REVIEW

2.1 Background

Agriculture plays a significant role in the economy and is considered as the primary source for the national income. Quality is considered as the fundamental parameter which is responsible for consistent marketing of crops. Ripeness is considered as the main quality indicator for many crops. The consumer (retailer or wholesaler) analyzes the quality of fruits based on their external or visual appearance. The external appearance of the fruit is used to estimate its ripeness, which is measured, by size, shape and color. Color is the most significant parameter out of these three parameters. It has an higher impact on the consumers' preference and quality. Certain colors are preferred in many agricultural products and results in higher selling prices. Colour is one of the most commonly used features to evaluate maturity for various fruits. Harvesting of fruits at the appropriate stage of maturity is of great significance for attaining desired level of quality. The level of maturity helps in the selection of storage methods, estimation of shelf life and selection of processing operations for value addition. The maturity has been divided into two categories i.e. physiological maturity and horticultural maturity. P*re-Harvest or Horticultural maturity* is the stage of development when a crop is suitable for harvesting. *Post-Harvest or Physiological maturity* is the stage when a crop is capable of further development or ripening after it is harvested i.e. appropriate for processing or eating. Quality characteristics such as flavor, texture and color are sustained when the fruit is harvested at an optimal stage of maturity[14][15]. Hence, ripeness controlling and monitoring have become a very important issue in the crop industry.

There are number of researchers who have presented their valuable ideas of ripeness estimation in the form of various algorithms and techniques[16][17]. Yin *et al.* [18], presented an automated technique on the basis of Red Green color difference for the segmentation process of an image. Xiang *et al.*[19], tested and figured out three segmentation techniques: multi-band ratio, RG and normalized RG. Yin *et. al* [20] utilized k-means clustering and L*a*b* color space for the segmentation of the ripe tomato. Wang *et al.* [21], analyzed two color spaces i.e. RG difference and hue average and it is concluded that results obtained for RG difference of images are better. The study has been conducted for recognition of ripe fruits. Also, there are chances of having unripe and ripe tomatoes together, so the proposed technique distinguishes between unripe and ripe tomatoes. The classification of unripe and ripe tomatoes is performed based on an Artificial Neural Network (ANN)[6]. The background illumination of the image is done on the basis of the RG difference. The main disadvantage of RG difference is its inability to separate green tomatoes as it is usually having a background of similar color. A segmentation method [22] is presented to segment unripe and ripe tomatoes from the back-ground under natural illumination. The specular reflection highlights on the tomato exterior have been removed. Therefore, this technique interpolates the neighboring colored pixels of the white pixel areas to maintain color integrity.

Arefi and Motlagh [23] presented a technique to classify unripe and ripe tomatoes by utilizing ANN. The background has been segmented on the basis of RG difference. The drawback of the proposed approach is its inability is to extract the green tomatoes from the complicated background. Grading of dates[24] is a crucial stage for producers and affects the evaluation of the export market and fruit quality. Mamdani Fuzzy Inference System (MFIS) has been used as a decision-making system for the classifications of the dates based on quality in this research. Two date parameters are considered for 500 dates: freshness and length. These date fruits are assessed by MFIS and results are compared with the manual process followed by a human expert.

Elhariri *et al.* [25], used the Random Forest (RF) and multiclass Support Vector Machine (SVM) and to determine the ripeness of bell pepper and tomato ripeness. An image dataset of 250 and 175 is collected for bell-pepper and tomato respectively. This proposed technique contains three phases: *pre-processing*, *extraction of features* and *classification*. In image preprocessing, images are resized and also removal of background is done. A feature vector is generated as a combination of nine color moments for HSV and histogram using Principal Component Analysis (PCA). Random Forest (RF) and multi-class SVM utilizing 10-fold cross-validation have been compared for classification of maturity phase. The outputs obtained for SVM are better as compared to RF in terms of accuracy.

Semary *et al.* [26] originated a classification system to classify infected/uninfected tomatoes based upon its external surface. The proposed technique has three stages; preprocessing, feature extraction and fusion and classification. Color moments for HSV and RGB channels have been used to derive the color information. The feature fusion method is based on a combination of texture and color features. Wavelets energy, Color moments, entropy and GLCM are considered. PCA is utilized to overcome the feature vector generated after feature fusion. This may lead to prevent the problem of dimensionality and save cost and time. SVM, Min-Max and Z-Score normalization are used for the classification of tomato images into two classes: uninfected/infected. Fuzzy Rule-Based Classification technique [27] is proposed to estimate the ripeness level of mango. Fuzzy logic is utilized to determine the different maturity stages of mangoes.

Goel and Sehgal [28] used a Fuzzy Rule-Based Classification technique to determine the tomatoes ripeness on the basis of color (R-G difference). MFIS is used to generate a classification system which can classify the tomatoes into six different ripeness stages. The training dataset comprises six ripeness phases of tomato. The main limitation is the size of the dataset as it should be larger and a sufficient number of training images should be available per class so that the performance of the system can be optimized. Another drawback is the requirement of improvement of the accuracy rate of segmentation to enhance the overall classification accuracy.

Food quality checking via dielectric spectroscopy determines a few interesting outcomes and unlocks the new prospects for effective consumption of food where quality is considered as a primary factor for the success of food industries. Khaled *et al.* [29] given a review which explains the basics of dielectric property and classification of measurement techniques of dielectric spectroscopy. It comprehensively describes the dielectric experimentations discovered for vegetables and fruits, along with the appropriate analytical modeling, sensing instrumentation approaches and conclusions. The detailed process of dielectric spectroscopy and its utilization in the electric classification of food products is described in detail. The problems faced in various applications should be targeted towards improved designs which should be adaptable enough to change based on the structural changes while heating or other physical interactions. It gathers a number of experiments that are tested, but further research should be continued for more accurate hypotheses and better conclusions.

Saberi *et al.* [30] proposed a method to determine color parameters of sweet cherries by using the combination of image processing and ANN techniques. The CCD camera is used for image acquisition. The image analysis is done through MATLAB software and ANN is used for modeling. To find the benefit of this method used, variations of color in cherry during ripening are analyzed. L* and b* attributes decreased according to the maturity of cherries and a* attribute increased at the initial stage and then later on decreased. Evaluation of L*, a*, and b* parameters describe the possibility of the reliable and relevant usage of the system for estimation of absolute color values of food materials as compared to Chromameter in terms of costs. By using this technique and based on previous research on the chemical content of cherries during ripening, extracting chemical features without destructive experiment is possible.

Blanes *et al.* [31] presented a study for evaluating the use of a robot gripper in the evaluation of firmness of mango and to build connections between the maturity of mango and the non-destructive robot gripper measurements with embedded accelerometers in the fingers. Intact mango is managed and manipulated by the robot gripper and some main attributes linked with their ripening index are evaluated. Partial Least Square (PLS) regression models have been proposed to describe these attributes based on the extracted variables from the accelerometer signals. According to this research, it is possible to evaluate the firmness of the mango fruit and ripeness level while handling with a robot gripper. Prabha and Kumar [32] proposed a technique to detect the maturity stage of fresh banana fruit by its color and size value of their images precisely. The mean color intensity from histogram; area, perimeter, major axis length and minor axis length from the size values, are extracted from the calibration images. Analysis of variance between each maturity stage on these features indicated that the mean color intensity and area features are more significant in predicting the maturity of banana fruit.

Mahayothee *et al.* [33] examined the performance of Near-Infrared Spectroscopy (NIRS) prediction models based on harvest year to estimate the quality of mango after harvesting. Diffuse reflectance spectra are used in the region of 700–1100 nm to establish calibration models for firmness, Titratable Acidity (TA), Ripening Index (RPI) using PLS regression analysis and Total Soluble Solids (TSS). The outputs show that the harvest year has a great impact on model robustness. When models from one harvest year are utilized for the prediction of data of other years, the high prediction error is found. Whereas using combined data for calibration immensely enhance the performance in terms of prediction accuracy. The results of prediction models based on past three-year data are better in terms of TSS, firmness, TA and RPI. The outputs signified the usage of NIRS as a reliable and constructive technique for quality assessment of mango. The more robust model can be prepared while considering the effect of the harvest year.

Nambi *et al.* [34] executed a study to determine the ripeness quality in mango fruit using RGB images. The main aim is to determine best image features to predict ripeness quality of mango using RGB images. The ripening period is categorized using hierarchical cluster analysis on the basis of color variations and textural properties. RGB images are collected at a different level of maturity stages and then feature extraction is done from the captured images. The predictability of various maturity phases with collected features are examined with discriminant analysis. It is observed from the results that features based RGB perform better in terms of prediction. These outputs are more appropriate for building a machine vision system to determine the ripeness level of mango by using simple RGB image.

McCool *et al.* [35] introduce a system for sweet pepper (capsicum) detection. The capsicum encounters various issues for the robotic system due to a higher level of occlusion and similar color of crops that of the background. To address these challenges, a technique is introduced to perform per-pixel segmentation and region detection. The result of the segmentation phase is utilized to determine the highly probable regions and declares these to be capsicum. The actual usage of Local Binary Pattern (LBP) is proposed to implement segmentation. It optimizes the accuracy of crop segmentation. The temporal information should be considered to reduce the number of false alarms and improve the detection rate.

Sa *et al.* [36] proposed Deep Convolutional Neural Networks based fruit detection system. The goal is to propose a fast, accurate and reliable detection system. It is the main component for the estimation of fruit yield and automatic harvesting.

The latest research has led to the development of an object detector named as Faster Region-based CNN (Faster R-CNN). It is adapted through transfer learning, for fruit detection using imagery obtained from two: Near-Infrared (NIR) and color (RGB). Fusion methods like late and early fusion are studied for combining the multi-model (NIR and RGB) data. This results in a multi-modal Faster R-CNN model, which achieves efficient outcomes. The proposed approach is faster to deploy for new fruits, as it works on bounding box annotation instead of pixel-level annotation and it improves accuracy. The model is retrained for the detection of fruits with the entire process. The new model is retrained each time per fruit.

Intra-class fruits recognition using pattern recognition and image processing methods is a difficult task as the sub-types of the same fruit shows similar behavior among each other and hence it is more difficult to distinguish when various varieties of fruits are considered. It becomes more challenging when the viewpoint of the camera also changes which results in changes in the characteristics of fruits. To solve this issue, Jana and Parekh [37] presented a solution for intra-class recognition of fruits by using the combination of both texture and color features based on Neural Network (NN) classifier. The proposed approach provides satisfying results even when the angle between the camera and the object of interest changes. It shows robustness, when fruits are present in a cluster and extraction of individual fruit shapes, are difficult.

A novel classification algorithm based on Radial Basis Probabilistic Neural Network (RBPNN) [38] is implemented and evaluated for classification of fruit surface defects in texture and color of orange. The proposed method takes images of oranges as inputs and then the texture and features of a defect portion are extracted by evaluating a gray level co-occurrence matrix and the defected portions have been classified using RBPNN-based classifier. The defects are categorized into groups: black mold (class 5), slight color defects (class 4), morphological defects (class 3), surface defect as bruises (class 2) and good fruit (class 1). Wajid *et al.* [39] include image features such as RGB color space and gray values based on Border/Interior pixel Classification (BIC) are extracted. The experimental results are performed by utilizing Naïve Bayes, Artificial Neural Network and Decision Tree.

Taofik *et al.* [40] proposed a system to work with the ability to detect one of the four maturity stages of chili and tomato. A novel method of training data acquisition is adopted in which the crops of chili and tomato have been observed from the time period of one month before harvesting. K-Means Clustering approach is used for image segmentation. Fuzzy logic has been used for ripeness detection. The output is classified into levels of ripeness: unripe, medium and ripe. It describes the preliminary outcomes of the testing system in partial and static conditions using a personal system before being deployed into a mobile-based integrated system.

Naik and Patel [41] given a detailed overview of the process of classification and grading of fruits[42]. Detailed observation of each step is done. Some feature extraction techniques like Histogram of Oriented Gradient (HOG), LBP and Speeded Up Robust Features (SURF) are considered with the commonly used features of fruits like texture, color, shape and size. Machine learning techniques such as ANN, K-Nearest Neighbor (KNN), SVM and Convolutional Neural Networks (CNN) are also considered. Methodology, pros, cons and challenges occurring in the classification and grading of food are discussed.

A study [43] is carried out with Indian mango cultivars to establish a ripeness model and associated index. The variations in physicochemical, color and texture features are calculated over the maturity period. The time period is divided into five phases: overripe, ripe, partially ripe, early ripe and unripe. Multivariate regression methods such as PLS, multi-linear and principal component regression are compared and calculated for its prediction. Multilinear regression model performs better in predicting the ripeness with 12 attributes. Cross-validation is performed to enhance the level of robustness and it is concluded that the expected ripening index is more suitable in predicting the ripening phases. The developed index and its multi-linear regression models are more effective in determining the ripeness of mango. The proposed models are further simplified using variable reduction techniques, for easy and quick prediction. The prediction can be performed in an effective way by using multi-linear models with 2 variables (acidity and total soluble solids) and 3 variables of color (external L^*, a^*, and b^*) coordinates.

Hazarika *et al.* [44] proposed a mathematical method applying Fourier-transform infrared spectroscopy to evaluate the ripeness of Cameo apple. The ripeness is calculated on the basis of the variation in concentrations of chosen elements in the fruit. The fruit samples are collected every 15 days from a single tree during the last 60 days of the ripeness cycle and then evaluation is done with Fourier-transform infrared spectroscopy. The vibrational bands from the Fourier-transform infrared spectra are committed to a definite functional group. A linear relationship is concluded between a number of days remaining before the apple fruit maturity and the peak intensities of the vibrational bands corresponding to a glucose molecule. The relationship has been utilized to evaluate the required time to reach a particular maturity level of fruit and to find the concentration of constituents at a particular growth cycle phase.

The grading of Papaya fruit is accomplished via the manual process and results in mis-classifications of papaya into boxes with various ripening phases[45]. The goal is to determine the ripeness of the papaya using random forests and digital imaging. A sequence of chemical or physical examinations have been performed and the actual maturity phase is calculated from pulp firmness readings. The hand-crafted color attributes have been derived from the peel via image analysis. Random decision forests are taken as input to predict the maturity stage. The cases are divided on the basis of pulp firmness and outputs represents that this internal attribute is connected to the fruit peel color. After image acquisition and analysis, seven groups of 21 color features are obtained and calculated. Two datasets for Random forests (prediction set and cross-validation) have been occupied for the experimentation. Through color image processing, acceptable outputs are disclosed for grading of papaya on the basis of pulp firmness.

Lecourt and Bishop [46] given an overview of regression and machine learning models which can be utilized in determining ripeness. The early analysis of fruit ripeness and prediction of the harvest yield and date by constructive technologies have the potential to reform farming practices. A number of informative approaches can be been used to determine the ripeness but not all of them are relevant for evaluation. This review targets the non-destructive methods which already have been applied to, the pre-harvest in-field measurements which include spectroscopic imaging, visible imaging, colorimetry and spectroscopy.

Bhargava and Bansal [2] originated the use of computer vision technology and image processing in the area of agriculture and food industry. The significant quality attributes of agricultural products are texture, shape, size, defect and color. To take over from manual assessment of food, the computer vision system is utilized which provide an authoritative, fair and constructive rating. It comprises mainly of four phases: *acquisition*, *segmentation*, *feature extraction*, and *classification*. The number of methodologies proposed by researchers is examined and correlated in each step.

There are various methods for color representation which include fuzzy logic, color mapping simple thresholding, statistical analysis and neural networks. Choi *et al.* [47], presented a Tomato Maturity Index (TMI) on the basis of hue value to calculate the degree of maturity in various phases of ripeness. The main objective of TMI is to generate a continuous index for all the maturity phases. The images of 120 tomatoes of various maturity stages have been collected for experimentation. Then, the extracted RGB values are converted to HSI color values. The TMI is calculated from the collected percent surface area below certain hue angles. The various maturity phases are considered: red, light red, pink, turning, breakers and green stages. There is an issue of misclassification which occur between turning and pink, green and breakers stages and light red and red stages. Mazen and Nashat [48] proposed four-class homemade database. An ANN based framework is proposed which uses color and development of brown spots. Tamura statistical texture features are employed to classify and grade banana fruit ripening stage. Sabzi *et al.* [49] proposed a new computer vision algorithm to detect the existing fruits in aerial images of an apple cultivar and estimate their ripeness stage among four possible classes: unripe, half-ripe, ripe, and overripe. The proposed method is based on a combination of the color features. A classifier is proposed based on ANN optimized with genetic algorithms.

Table 2.1 summarizes the work done by various researchers on the problem addressed. It is concluded via a comprehensive survey conducted that although a number of researchers have planned the different approaches for the quality analysis of fruits still there is a need of developing a robust computer vision based system.

Table 2.1: Methods and Tools Used in the Existing Work

Authors	Year	Fruits Considered	Work Done
Wang *et al.* [21]	2013	Tomato	RG difference and hue average have been compared and concluded that the performance is better in terms of RG difference.
Arefi and Motlagh[23]	2013	Tomato	Classification of tomato into two classes i.e. ripe and unripe based on ANN.
Alavi [3]	2013	Dates	MFIS is used as a decision-making method to classify the dates based on quality.
Gupta and Sehgal [22]	2014	Tomato	Segmentation method to extract unripe and ripe tomato from the complicated background.
Elhariri *et al*. [25]	2014	Tomato and bell pepper	RF and Multiclass SVM for the determination of bell pepper and tomato ripeness.
Mansor *et al*. [6]	2014	Mango	Fuzzy rule-based classification technique to estimate the maturity phase of mango.
Semary *et al*. [26]	2014	Tomato	A classification system to classify tomato fruits into the infected/uninfected class according to its external surface.
Goel and Sehgal[28]	2015	Tomato	Fuzzy Rule-Based Classification System to determine the ripeness on the basis of the color of tomatoes.
Khaled *et al.* [29]	2015	Fruits and vegetables	A review describes the dielectric property basics and classification of measurement techniques of dielectric spectroscopy.

Authors	Year	Fruits Considered	Work Done
Saberi *et al.* [30]	2015	Cherry	Estimate the ripeness level of sweet cherries based on ANN techniques.
Blanes *et al.* [31]	2015	Mango	The usage of robot gripper to assess of mango firmness in order to predict the maturity stage of mango.
Prabha and Kumar [32]	2015	Banana	Proposed a technique to detect the maturity stage of fresh banana fruit by its color and size value of their images precisely.
Mahayothee *et al.* [33]	2016	Mango	Analyzed the effect of harvest year on NIRS prediction models to evaluate postharvest mango quality.
Nambi *et al.* [34]	2016	Mango	Determine best image features for estimation of mango ripening quality.
McCool *et al.* [35]	2016	Sweet Pepper	Crop detection system developed for the detection of sweet pepper.
Sa *et al.* [36]	2016	Multiple Fruits	Faster R-CNN for fast and reliable fruit detection approach.
Jana and Parekh [37]	2016	Multiple Fruits	Viewpoint invariant solution for intra-class recognition of fruits by using texture and color features based on NN classifier.
Capizzi *et al.* [17]	2016	Orange	A classification approach based on RBPNN is used.
Taofik *et al.* [40]	2017	Tomato and chili	System to work on a mobile device with an ability to detect four levels of chili and tomato ripeness.
Naik and Patel [41]	2017	Multiple Fruits	A detailed overview of fruit classification and grading system. Detailed examination of each step is done.

Authors	**Year**	**Fruits Considered**	**Work Done**
Capizzi *et al.* [20]	2017	Mango	Build a ripeness index and associated model.
Hazarika *et al.* [44]	2017	Apple	Mathematical method applying Fourier-transform infrared spectroscopy to determine the maturity level of Cameo apple on the basis of the variations in the concentrations of chosen elements in the fruit.
Pereira *et al.* [22]	2018	Papaya	Hand-crafted color features are evaluated from the peel via image analysis. Random Decision Forests are used for the prediction of the maturity stage.
Lecourt and Bishop [46]	2018	Multiple Fruits	An overview of regression and machine learning models used in ripeness estimation.
Bhargava and Bansal [2]	2018	Multiple Fruits	Proposed the utilization of computer vision technology and image processing in the area of agriculture and food industry.
Mazen and Nashat [48]	2019	Banana	Proposd four class based technique by utilizing ANN.
Sabzi *et al.* [49]	2019	Apple	Proposed a new technique based on ANN optimized with genetic algorithms to detect the existing fruits in aerial images of an apple cultivar.

Chapter 3
PROBLEM STATEMENT

3.1 Gap Analysis

Till now, optimal harvest date and period of storage of fruits is estimated manually by human graders by examining the visual appearance of the fruit based on a classification chart and practical experience. However, subjectivity is the main issue in the manual estimation of ripeness. Tiredness can also be one factor which can hamper the effectiveness and accuracy. It is a cumbersome and time-consuming task in case of big greenhouses and farms. Hence, the automation process of ripeness estimation will result in a big advantage for the agriculture industry and will minimize the inconsistencies in the manual estimation of ripeness. The research work on fruits harvesting robots is carried out more than 20 years ago but still, these reported works have not been used practically[50]. The main reason is minimal or no difference in the speed of robots and manual process. It is very expensive due to hardware costs. But with the advent of data storage and acquisition techniques, the work in this area especially harvesting robots has gained a lot of attention again and is considered as an emerging research area among researchers [14–17]. The latest innovations are leading towards the fulfilment of the demand for innovative methodologies in the agriculture industry without any interference in the natural growth of the crop [15].

The latest innovations and developments in the agriculture industry leads to the need of innovative techniques which do not interfere in its natural growth and leave the crop intact. The study has been conducted with a view to design and implements a ripeness prediction technique for the harvesting which can recognize all the ripeness phases of fruits.

Based on the reviewed literature and existing work of various researchers, the following research gaps have been identified [14-49]:

- The complicated background of the dataset is not considered. For instance, there can be an unripe fruit of green color having a similar colored background. It is difficult to distinguish between the leaves, branches and actual fruits.
- There is a problem of misclassification between breakers and green stages, between ripe and turning stages in most of the approaches.
- The image dataset which was considered in different research works has not been realistic. Usually, an image of a single fruit is considered. But in the real world, there can be scenarios in which there are number of fruits hanging over the same branch having overlapping and hidden areas. There can be a case in which there is a number of fruits having different ripeness stages in the same image.
- Different color spaces have been utilized for color feature extraction, still there is a need to explore combination of other color spaces as well to optimize the performance.
- It can be summarized from the existing work reported that the images from different regions can be included in order to make the system regional bias-free.
- As per literature, disease recognition, vegetable and fruit grading and sorting are performed on a single fruit. There is a need of a generalized system which can sort or grade the fruits and detect the defects of multiple vegetables and fruits.
- There is a need to develop an automated system to sort fruits based on different levels of maturity. The robustness of ripening prediction can be increased by further investigation. This can be optimized by using variants of machine learning or using deep learning which can automatically extract the information from images automatically without manual intervention.
- It may be possible to proposed and develop a generalized mathematical model by increasing the frequency of observation and by studying the additional food crops based on ripening phase.

- There is a need to incorporate temporal information to reduce the number of false alarms and improve the detection rate.

3.2 Problem Statement

Sourcing skilled farm labor is considered as one of the most cost-demanding factors in agriculture industry. There are various factors which lead to this problem such as water irrigation, the rising values of supplies, power and agrochemicals etc. This is driving horticultural industry and farm enterprises to be under pressure with only small profit margins. Still, food production needs to satisfy the growing demands of an ever-growing world population in these challenging situations and this result in a critical problem.

Automated harvesting can provide a potential solution to this problem by increasing fruit quality and reducing the costs of labor. Due to these reasons, there has been growing interest in the use of agricultural robots for harvesting vegetables and fruits over the past three decades. The development of such techniques and platforms has number of challenges such as detection, manipulation, recognition and picking. However, the development of an efficient fruit detection and ripeness estimation system is an inportant step toward fully-automated harvesting robots, as this is the front-end perception system before subsequent grasping and manipulation systems; if the fruit is not detected or seen, it cannot be picked. Secondly only the ripe fruits must be picked. There are number of challenges in this step due to various factors, such as occlusions, illumination variation or fruit possess a similar visual appearance as that of a background.

The works related to fruit recognition and ripeness prediction as discussed in literature has been carried out using machine learning models only without considering the fuzziness in the nature of the underlying problem. Usually, researchers have taken just one or two fruits. The size of the data set which they have considered is also very small. These techniques cannot be used to estimate the ripeness of fruits before harvesting.

Color is considered as the most significant parameter to estimate the ripeness of the fruit and has a high influence on the consumer's preference and quality.

Therefore, the proposed approach focuses on three research motivations. First, to develop a ripeness based classification technique which can detect all the four ripeness stages of the fruits. Second, the system must be able to detect the ripeness of fruit without interfering in its growth under natural conditions. Third, while segmenting the fruit from the background, the color integrity must be sustained so that a minimum information loss occurs.

The primary aim of this thesis is to propose a technique in which an image of the fruit should be taken as input and ripeness stage of the fruit is depicted as output. The output can be one of the four ripeness stages: *Unripe, Breaker, Turning* and *Ripe.* Color based features are taken as input features as color is taken as the most favorable feature for decision making by the customer. Two approaches are proposed in this research work to address the issue. In this research, we intend to address the following questions:

- How to deal with a complicated background having a similar color as that of the fruit?
- How to extract the object of interest from the input image?
- Which features or factors can be used to determine the ripeness of the fruits?
- How to determine the ripeness stage of the fruit?

The proposed work will help the farmers or users to determine the ripeness stage of the fruit without inspecting the fruits manually. It will reduce the harvesting time of the user as he/she will just pick the ripe fruits. It will provide the unbiased results to the users as compared to the manual approach as there are chances of misclassification of fruits in later case. The proposed approach can be implemented without any interference in the natural growth of the fruits. The proposed solution enables us to obtain an efficient and fast classification system for fruits. Although it is in the early stage of development, still such a system can be proposed on large scale for industrial applications.

3.3 Objectives of the Proposed Work

On the basis of identified research gaps and research motivation, the proposed work entitled "*Efficient Pre-harvest Ripeness Estimation Techniques for Fruits*" has been accomplished through various research objectives. The broad objectives of this research work are:

1. Study and analyze the various existing fruit ripening prediction or estimation approaches.
2. Develop a pre-harvest ripening estimation technique for fruits.
3. Validation and comparison of the proposed technique with the existing approaches.

Chapter 4

PROPOSED WORK

To address the problem of pre-harvest ripeness estimation, two techniques have been proposed: ANFIS based Pre-harvest Ripeness Estimation (APRE) technique and Faster R-CNN based Ripeness Estimation (FRRE) technique. Section 4.1 and Section 4.2 present the proposed APRE and FRRE techniques respectively.

4.1 Proposed ANFIS based Pre-harvest Ripeness Estimation (APRE) Technique

In this research, an efficient *ANFIS based Pre-harvest Ripeness Estimation (APRE)* technique for fruits has been proposed to estimate the ripeness of fruits based on color. In this section, a brief overview of the proposed methodology is presented. The proposed technique is divided into three tasks: *Data Analysis and Processing, Input Feature Selection based on Classification Accuracy and Fuzzy Logic Implementation* as shown in Figure 4.1. The detailed explanation of each phase is presented in further sub-sections (Section 4.1.1 to 4.1.3). In the first phase i.e *Data Analysis and Processing*, data set of images of fruits is prepared in the image acquisition phase. Then images are pre-processed to make them equal in size. In Image Segmentation phase, fruits are extracted from the background. The two-color depictions: red-green color ratio and red-green color difference are calculated based RGB color information which has been extracted. These depictions are then compared as a criterion for classification accuracy using various classification algorithms such a K-NN, SVM and Decision Tree.

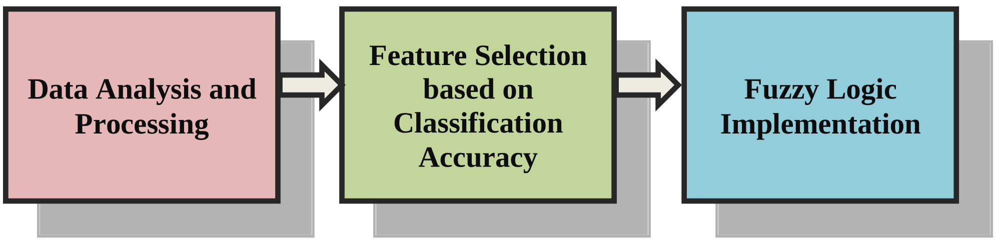

Figure 4.1: Phases of the Proposed APRE Technique

In the proposed technique, Adaptive Neuro-Fuzzy Inference System (ANFIS) is utilized to develop the fuzzy rule-based classification technique which classifies the fruits into four maturity stages namely *Unripe, Breaker, Turning* and *Ripe*. The dataset is generated by collecting the images from ImageNet[51][52] for experimentation. 70% of the input images are used for training and 30% images of the total are used for testing respectively. The training dataset is classified into four classes representing the four different stages of ripeness. In this section, a brief overview of the proposed methodology is presented as shown in Figure 4.2.

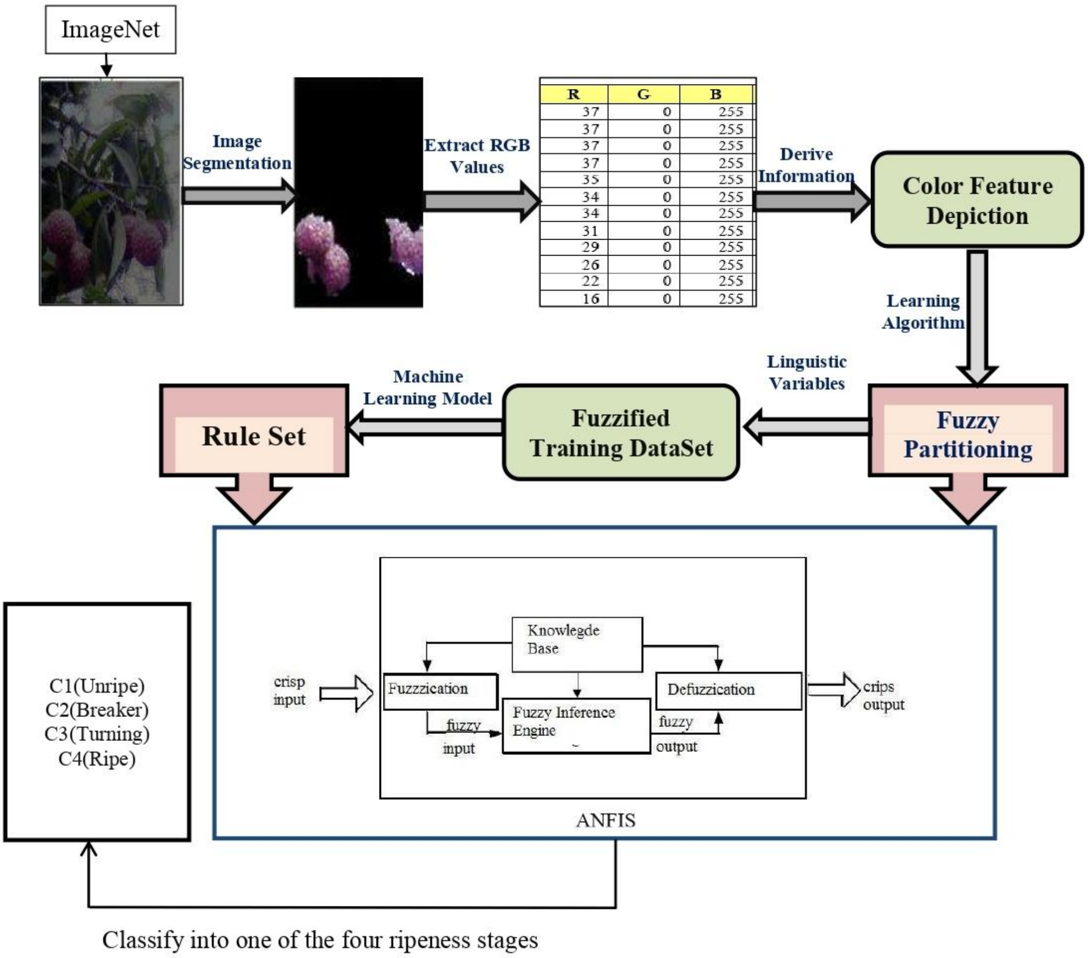

Figure 4.2: Workflow of the Proposed APRE Technique

Generally, there are two kinds of features which are used in such types of techniques: Red/Green Ratio and Red-green color difference. The classification accuracy of these two parameters needs to be analyzed so that the better feature can be selected as an input feature for the proposed work. As this kind of application is generally fuzzy in nature, so the machine learning models cannot be applied directly without dealing with the fuzziness of the problem. However, the number of initial fuzzy partitions is based on a user-defined variable, which is the biggest drawback of conventional fuzzy logic based inference system. So, there is a need for an adaptive system which can automatically tune the initial fuzzy partitions. Automatic fuzzy partitioning of the features space into linguistic terms should be performed by utilizing Adaptive Network Fuzzy Inference System (ANFIS) as a decision-making technique to classify the fruits based on the input feature vector. The problem considered should provide an automatic decision-making harvesting system without the help of a human expert.

4.1.1 Data Analysis and Processing

The task of data analysis and processing[53][54] is further divided into three tasks: image acquisition, pre-processing and image segmentation process as shown in Figure 4.3.

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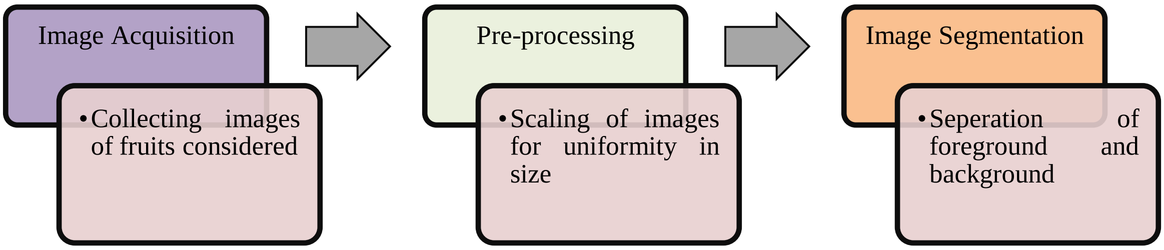


Figure 4.3: Workflow of Data Analysis and Processing Phase

In image acquisition phase, various kinds of fruit images are collected. Around 2832 images are taken as dataset. The data set has mature, immature and partially mature fruits which are connected, overlapped and partially covered by leaves and branches as shown in Figure 4.4. The primary task of the proposed system is to recognize the fruits by segmenting the fruits from the background. The background of the fruit can be complicated as it may consist of plants, branches and leaves.

In pre-processing phase**,** the data set consists of the images which are of different sizes, so these images are first scaled to the uniform size to fasten up the calculations. The size of the image is 1296 x 964.

(a) Unripe (b) Breaker (c) Turning (d) Ripe

Figure 4.4: Sample Images of Fruit Dataset

In image segmentation phase, an efficient technique is applied to extract the fruits from a complicated background. The segmentation technique has two phases. The first phase deals with color space selection to separate out the required pixels i.e. pixels which are part of the fruit and the second phase includes clustering techniques to cluster those identified pixels in an image. The process of classification comprises two phases: *color feature representation* and *color categorization*. Color should be represented in such a way that it can be categorized. The commonly used Color spaces in such kind of applications include L*a*b*, RGB and HSI etc. The main objective of color categorization is to classify the fruits based on color.

In the case of RGB color space, there is no need to perform any conversion process. Whereas, L*a*b* color space is more suitable as it depicts similar to the human process of visualizing the color. There are number of approaches which have been proposed based on the difference between red and green components in RGB color space.

Once the required pixels are recognized, the next task is to cluster these pixels together. The commonly used clustering techniques include automatic threshold segmentation based on Otsu's threshold, constant threshold segmentation, neural network and K-means clustering etc. The process of image segmentation is depicted in Figure 4.5.

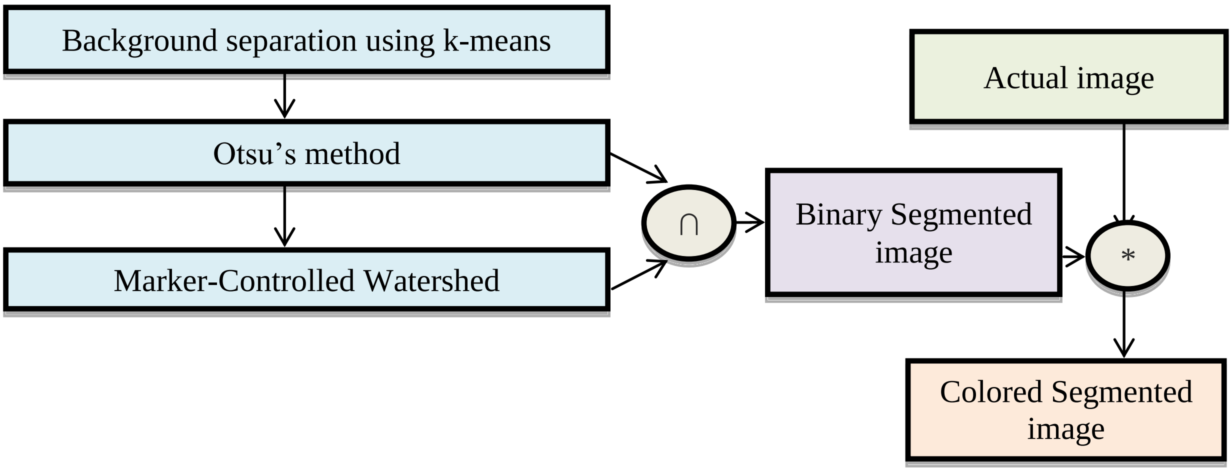


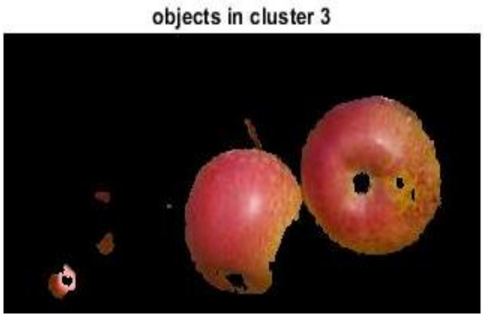
Figure 4.5: Flowchart of Image Segmentation Process

The Segmentation technique used in this work consists of two phases. Initially, the foreground and background image are separated in L*a*b* color space using k-means clustering[55]. The main objective is to extract the colored image of the fruits from the background. Figure 4.6 (a),(b) and (c) show the input image file and output image files for k-means clustering algorithm which is used for background separation. The image is then converted to a binary image from colored image based on the adaptive Otsu's method[56] that results in good segmentation as compared to the existing approaches. Figure 4.7 (a) and (b) shows the input image file and output image file for adaptive Otsu's method which is used for converting the input image to the gray-scale image. Watershed segmentation[57] is used to separate the touching and overlapped fruits. It is utilized over the single channel of the image. The selection of the channel is done dynamically on the basis of the maximum threshold value.

Figure 4.8 (a) and (b) shows the input image file and output image file for Marker-Controlled Watershed method which is used for detection of edges and overlapped areas. Finally, the intersection operation is performed on the two images obtained from watershed segmentation and adaptive Otsu's threshold to obtain the final binary-segmented image. Figure 4.9 shows the output Binary Segmented Image file which is obtained by applying the intersection operation on the output of Otsu's method and Watershed method. The binary image and the original image are multiplied in order to reconstruct the colored segmented image.

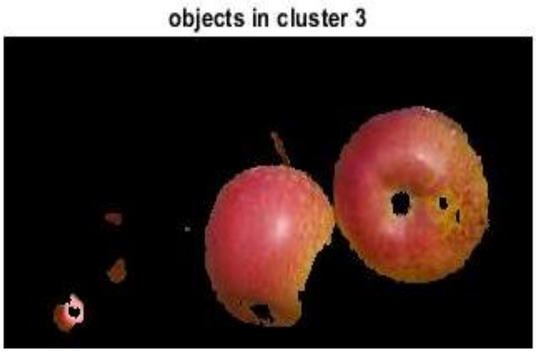
(a) Input File

(b) Background Separated Output File 1

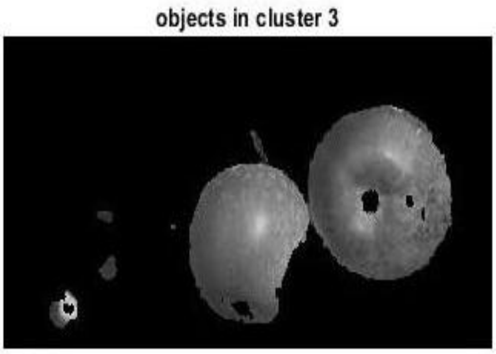


(c) Background Separated Output File 2

Figure 4.6 (a-c): Input and Output of the Background Separation Step

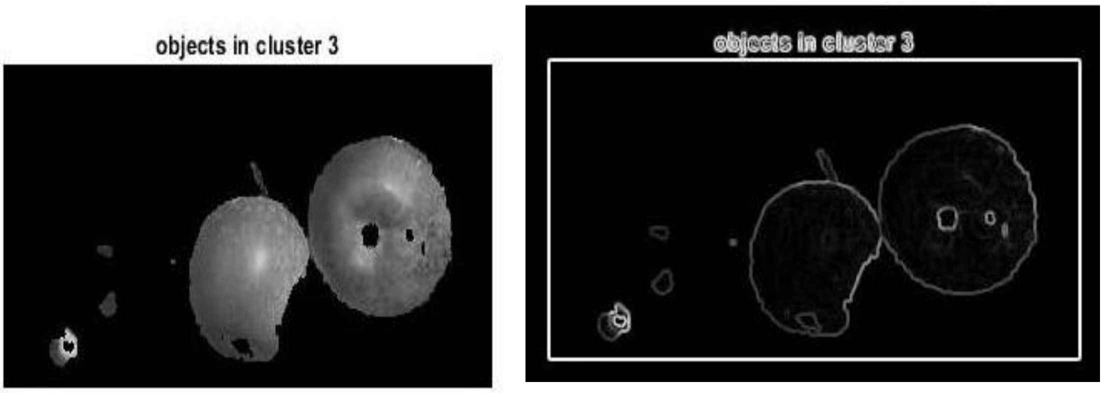


(a) Input File



(b) Output File

Figure 4.7 (a-b): Input and Output of the Otsu’s Method



(a) Input File (b) Output File

Figure 4.8 (a-b): Input and Output for Marker-Controlled Watershed

Figure 4.9: Binary Segmented Image File

4.1.2. Feature Selection based on Classification Accuracy

There are various color feature depictions such as HSV, L*a*b*, RGB and HSI etc for the image. In the initial ripening stages, fruits comprise high intensity of green color and very low intensity of red intensity. The intensity of red color increases and green color decreases as the ripening of the fruits starts. Hence, Red, Green and Blue values are obtained for an image which is obtained from the segmentation step. Based on these RGB values, two color feature depictions viz. Red/Green(R/G) ratio and Red-Green(R-G) difference are calculated. There are two advantages of these features: There is no need to do conversion operations as the RGB color space is utilized and signals consist of RGB components only. Second, both the color feature depictions R-G and R/G show linear behavior with respect to the ripeness stages and helps in better understanding of different stages. The average value of green and red components is computed based on the extracted RGB values. Red-green difference and red-green ratio are calculated based on Equations (4.1) and (4.2) as follows:

$$\mathrm{R-G} = \mathrm{mean}\left(\mathrm{I}\,(:,:,1)\right) - \mathrm{mean}\left(\mathrm{I}\,(:,:,2)\right) \tag{4.1}$$

$$\frac{\mathrm{R}}{\mathrm{G}} = \mathrm{mean}\frac{(\mathrm{I}\,(:,:,1))}{\mathrm{mean}}\left(\mathrm{I}\,(:,:,2)\right) \tag{4.2}$$

Where, $I(:,:,1)$ and $I(:,:,2)$ are the red and green components of an image I respectively. The performance analysis and comparison of both color features are presented in the Results (Section 5). It can be concluded from the result section that R-G difference is better as an input feature for the proposed technique.

4.1.3 Classification using Fuzzy Rule-Based Decision System

The ripeness of the fruit is basically fuzzy in nature. The color changes from green to light-green to pink to the tones of red gradually. There is no crisp value or threshold value based on which decision on the ripeness of fruit can be taken. Hence, this problem can be solved by using fuzzy. The computation of the input data for ANFIS is conducted using Matlab.

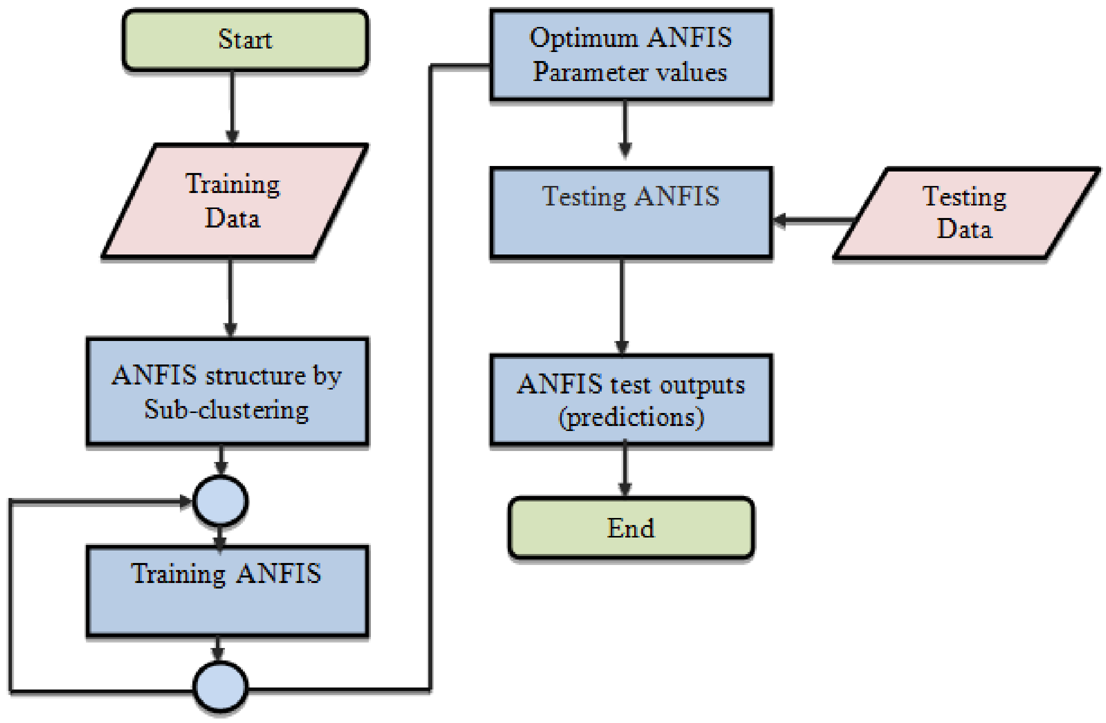


Figure 4.10: Flowchart of the ANFIS Algorithm

The main computation procedure of ANFIS includes four steps. Data input is first step. The experimental data comprises output and input data. Input data is the Red-Green difference parameter, while output data is the ripeness class to which the fruit belongs. Fuzzy sets are assigned in second step. For the data input, several fuzzy sets should be assigned to each kind of input and output data.

The membership functions of the system will be adapted based on the range of data and fuzzy sets in the data processing phase automatically. The third step, ANFIS training function is used for the training of the input data. The training of the data is automatically performed in the system and an array of training errors is generated. The output prediction is the last step. After training, an ANFIS model of the ripeness system is generated for output prediction. The results of the prediction are obtained efficiently by providing the parameters and utilizing the predicting function.

In the ANFIS, the data set is divided into two parts as training and test data [24]. The ANFIS structure is generated using Sub-clustering automatically. The training phase is an iterative process, in which the optimum values of the system parameters are calculated by minimizing the sum of squared differences between training data values and model predictions. The hybrid method is utilized for the training phase. The algorithm of ANFIS is shown schematically in Figure 4.10.

In the first step in ANFIS, the input parameters are fuzzified using an appropriate partitioning technique. Sub-clustering technique is utilized and input variables are fuzzified. In the second step, the first-order Sugeno Fuzzy Inference System with linear output function is selected as the inference system. Later, the ANFIS structure is completed by the selection of a hybrid learning algorithm. Then fuzzy rules are generated for the inference system. In the rule-base, fuzzy variables are connected with fuzzy AND operators and the max-min decomposition technique is used to associate rules. Furthermore, training is continued for epochs and process is terminated when the stability in error decrement is observed. In the proposed technique, fruits are segmented from the captured images under complicated background, while at the same time the color integrity of the image is also maintained. Hence, the work presented provides the self-sufficient decision-making system.

4.2 Proposed Faster R-CNN based Ripeness Estimation (FRRE)

Technique

In this work, a real-time fruit ripeness estimation technique i.e. Faster R-CNN based Ripeness Estimation (FRRE) technique is proposed by utilizing the concept of Deep Convolutional Neural Networks (DCNN) which can generalize and perform efficiently in different tasks with pre-trained attributes. There is a huge advantage of using this technique as it can easily adapt to various types of fruits and various types of ripeness stages with a minimum number of training images. Both qualitative and quantitative outcomes are demonstrated and compared to previous work for the evaluation. The main contributions of this research work are as follows:

First, is to develop an efficient pre-harvest ripeness estimation technique based on R-CNN for fruits which can be trained with a small dataset quickly. R-CNN is pre-trained based on a large dataset such as ImageNet[51]. Second is to accurately identify the fruit from its complicated background. The background may have similar color as that of fruit or there may be overlapped and connected areas. The input image dataset has been collected for both night and day.

4.2.1 Fruit Classification based on Ripeness using Faster R-CNN

There have been recent advancements being made based on deep convolutional neural networks on large-scale image classification but, accurate classification is still a challenging problem in the machine learning and computer vision areas. This task needs the detection of the objects in an input image as well as the locations at which these objects are located. So, there is a need for an accurate region proposal techniques in this task. The main focus of this research work is to detect the fruit and then classify its ripeness stage.

There have been recent works in these areas such as EdgeBoxes [58] which utilizes the edge information to obtain region proposals and selective search [59], which combines superpixels on the basis of low-level features. However, the running time of these methods is similar to that of detection to hypothesis object locations. Faster R-CNN [48] has been utilized to overcome this issue by introducing the Region Proposal Network (RPN). The convolutional features are shared between RPN and classification network. Both of these networks have been merged as a single network which can be trained and tested as a throughout the process. In this way, the running time will be lesser in region proposal generation and an effective detection rate can be maintained. This blend outperforms the existing classification techniques in terms of accuracy.

Faster R-CNN utilizes [48] color images (RGB) to perform general object detection and classification. It comprises two phases: (i) region proposal; and (ii) a region classifier. The region proposal phase generates a set of N_P proposed bounding boxes (regions) where the objects of interest can reside within the image. The main task of the region classifier phase is to determine if the region which is under consideration has the object of interest or not. The classifier can be a binary-class or *N*-class classifier. To train the Faster R-CNN for the proposed work, fine-tuning is performed [60]. This step needs requires labeled bounding box information for each of the classes to be trained. An example of the required bounding boxes is given in Figure 4.11.

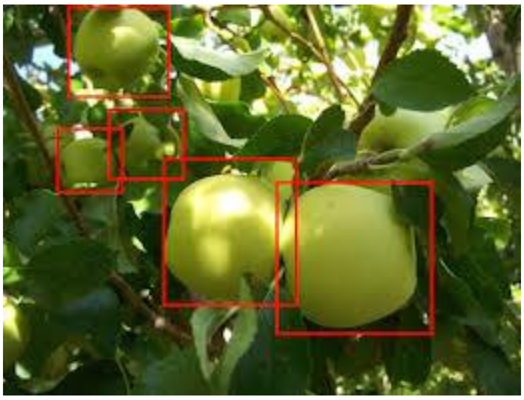


Figure 4.11: Bounding Boxes of Input Image

The test-time detection pipeline of Faster R-CNN is illustrated in Figure 4.12. Initially, the regions of interest are obtained from the input image and then these are provided as input to subsequent convolutional layers. VGG-16 model has been utilized and it has 13 convolutional layers. The region proposals are created by RPN based on the pre-generated feature map. These proposals highlight the regions which are having higher chances of containing an object of interest. The softmax classifier and fully-connected layers yield n bounding boxes, B_n and their respective probability scores of each class, $P(X|\mathbf{B}_n)$.

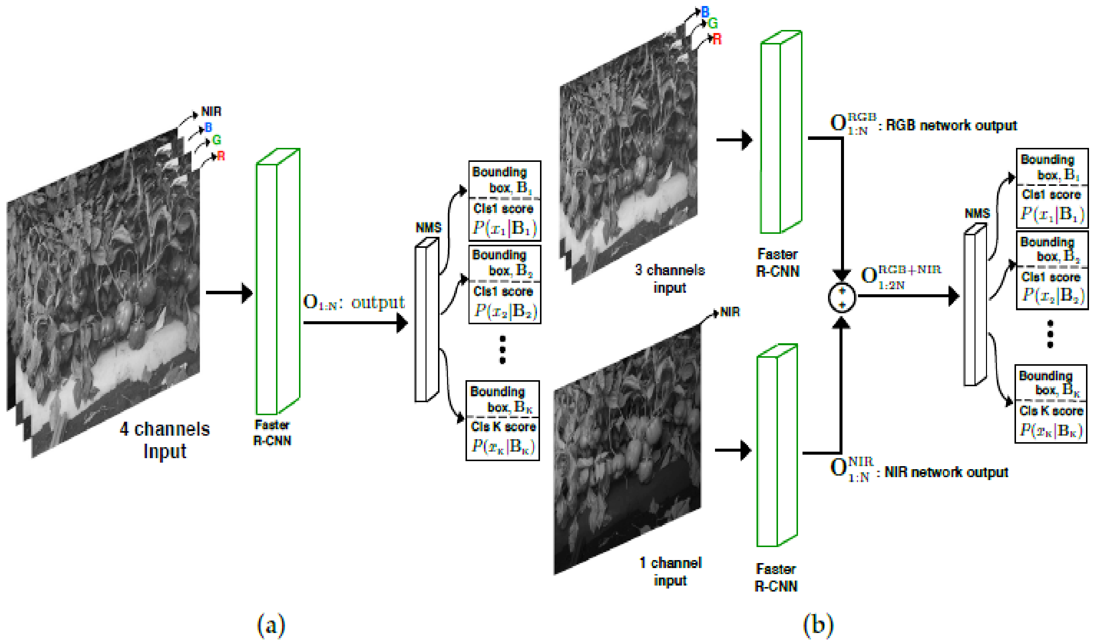


Figure 4.12: Test Time Detection Pipeline of Faster R-CNN

There are two fully-connected (Fc6 and Fc7), thirteen convolutional layer and one softmax classifier layers as presented in Figure 4.12. The number of proposals is denoted by N=300. $O_{1:N}$ denotes the output which comprises N bounding boxes and their scores. Non-Maximum Suppression is calibrated to 0.3 removes duplicate predictions. BK is a bounding box of the Kth detection that is a 4×1 vector containing the coordinates of top-left and bottom right points. x_K is a scalar representing an object being detected. The use of neural networks can extract the important features of discriminatively.

Figure 4.13(a) is the visualization of the first convolutional layer of the color VGG-16 network. This model is based on 3 × 3 convolutional kernels (mask) and a 2 × 2 pooling mask from the end to the end of 13 convolutional nets. Filters have greenish and reddish colors that correspond to unripe and turning fruits. Other filters represent edge filters in varying orientations. The input data layer is shown in Figure 4.13(b) shows. The cyan boxes are manually labeled in the data input layer to mark the corresponding fruits of the feature map. The feature maps from the conv5 layer are presented in Figure 4.13 (c). It can be seen that the regions for required objects are strongly activated and this information is very useful for classification process and RPN.

(a) (b) (c)

Figure 4.13: Filters and Feature Activations of conv5 Layer (a) The 3 × 3 (pixels) Conv164 filters of the RGB network from VGG, (b) The input data and (c) One of the feature activations from the conv5 layer.

A high-dimensional feature space can be visualized to investigate the performance of the proposed technique. The output generated from the fully-connected layer is utilized as feature representations for classification tasks [51] and this feature is discriminative. The fully-connected 7 (fc7) layer provides dimensions of feature vectors to t-Distributed Stochastic Neighbour Embedding algorithm (t-SNE) [61] with the respective labels. t-SNE is considered as one of the significant dimensionality reduction techniques. In this, pairwise neighboring similarities are measured based on the L2 norm distance in both low and high dimensions. The low dimension (2D) feature visualization using t-SNE is presented in Figure 4.14. Each feature is represented as a point and color is considered as the corresponding label. Turning and Ripe fruits are distinguishable from each other and the background as well. This figure also shows that good detection results are expected given a reasonable classifier. The dimensions of features are extracted from the Fc7 layer and visualized in 2D. For the visualization, 86 images are randomly selected from the dataset and processed for the network shown in Figure 4.14. In case of (VGG-16) model, the depth of the network plays significant roles for proper detection performance and despite its slightly inferior classification power, its features generated from the network architectures outperform other existing networks, such as GoogLeNet[62], AlexNet [52] and ZF[63]etc.

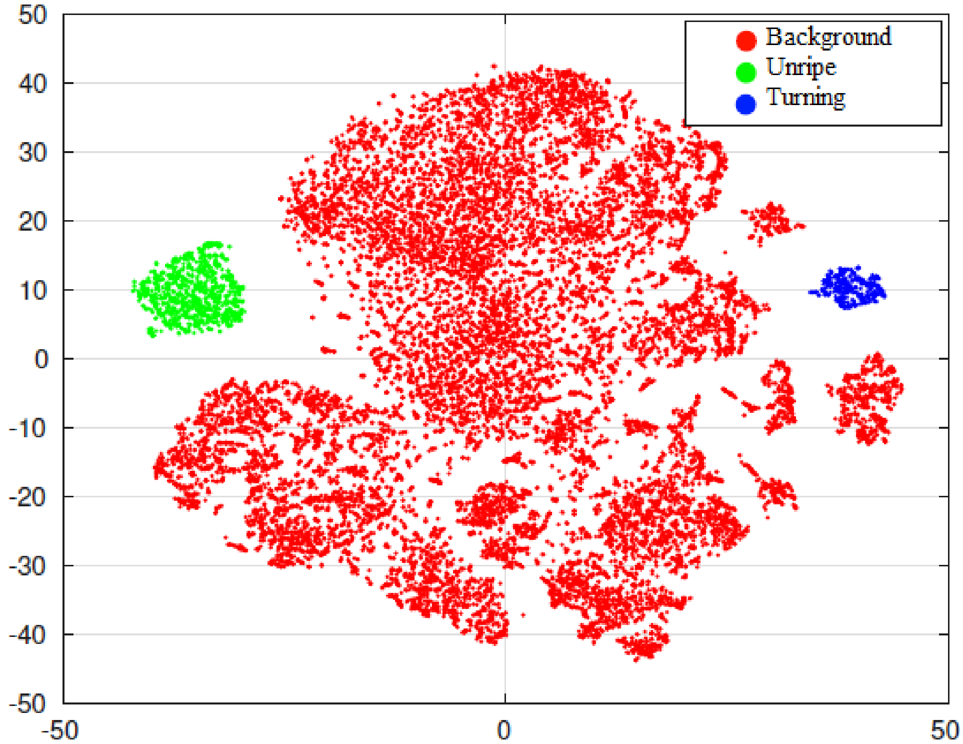


Figure 4.14: t-SNE Feature Visualization of 3 Classes

Therefore, VGG-16 model is the most popular choice in the machine learning and computer vision fields for the front-end feature extraction module. These feature maps are used by Faster R-CNN as guidance as where to look. The process of training VGG-16 net and its deployment for ripeness classification are presented in the following section.

4.2.2 FRRE Training and its Deployment

For the stated problem, Faster R-CNN has been fine-tuned. Fine-tuning consists of adapting or updating the parameters of the model based on the new data. In practice, this involves initializing a new classification layer and updating all of the layers, for both the classification and region proposal network. The classification network is similar to that of VGG architecture [64], as it provides the best performance.

The network configuration of VGG is based on Configuration D, in which there are 13 convolutional layers. These layers are followed by two fully-connected layers, referred to as VGG-D. The original implementation of Faster R-CNN was fine-tuned using the PASCAL VOC dataset. The network has been initialized by the pre-trained ImageNet dataset, which consists of 1.2 million images, 1000 object categories and their bounding box annotations. Hence, there is a need to fine-tune the network again using the custom data; otherwise, Faster R-CNN will detect the 20 ordinary objects, based on which the network is trained, such as bird and dog, etc. By doing this, the features learned from a large-scale dataset can be utilized which are well generalized to different visual recognition tasks. The performance analysis of FRRE technique has been done in chapter-5 which clearly shows that the proposed FRRE technique outperforms the other techniques.

Chapter 5
EXPERIMENTAL RESULTS

5.1 Experimentation Results of Proposed APRE Technique

The analysis is done on three different color feature representation R-G, R/G and avgRGB for all the images of fruits stored in the database. Two color depictions R/G and R-G are selected for the experimentation based on their behavior, as discussed earlier in Section 4.1.2. The color depictions have been compared in terms of classification accuracy. It can be concluded that R-G performs as compared to the R/G during experimentation, so R-G is selected as the color depiction feature for the proposed technique. The implementation of the fuzzy inference system is done using MATLAB. The detailed analysis of accuracy for each of the four ripeness classes is also discussed for the proposed techniques. In order to evaluate the proposed techniques, the sample dataset of fruit images is randomly partitioned into two sub-parts viz. 70% of the dataset is used for training and 30% of the dataset is used for testing.

5.1.1 Analysis of Color Feature Representations

The averages of each color component for all the fruit sample images in the RGB color model are calculated for the analysis. Figure 5.1 shows the changing trend of averages of Red (avgR), Green (avgG) and Blue (avgB) color components at various maturity phases. With the increase of maturity, the average red tends to increase while the average green tends to decrease. At the unripe and breaker stage, the value of green does not show significant change. Henceforth, the average of red or green is not sufficient alone for distinguishing among the maturity phases. Figure 5.2 and Figure 5.3 show the changing trend of R-G and R/G features. The variations of red-green difference and red-green ratio show a linear growth. When there is a change from breaker to turning stage, both red-green ratio and red-green difference show a significant change. Hence, both the color depictions are appropriate for estimating the maturity phase.

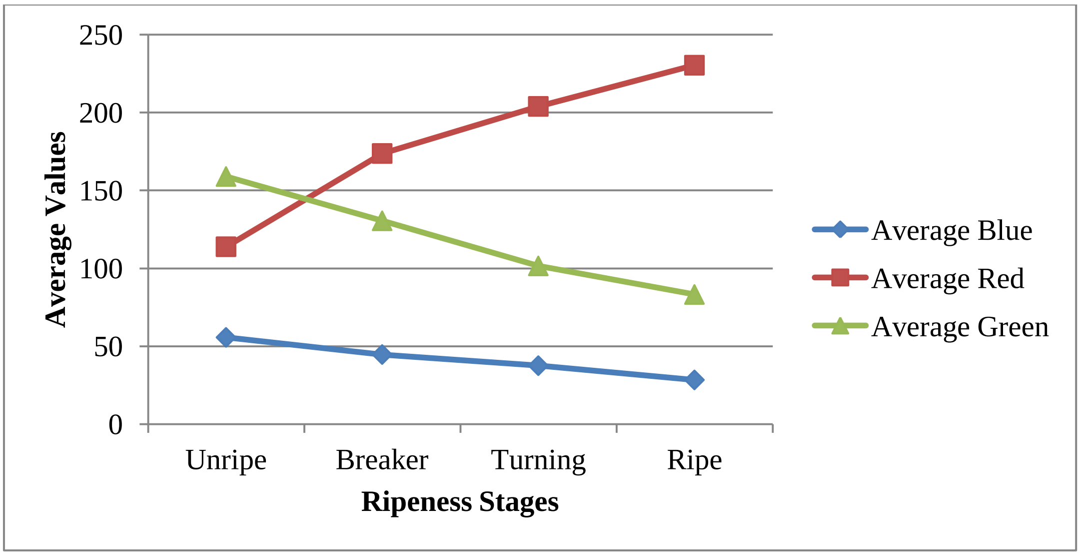


Figure 5.1: Behavior of avg R, G and B Component Values of the Images for Four Ripeness Stages

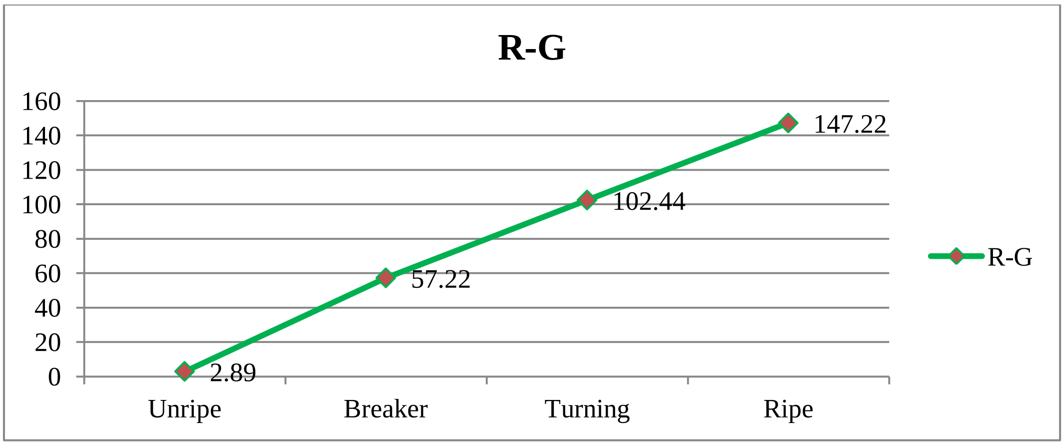


Figure 5.2: Behavior of Average R-G Values of the Fruit Images for Four Ripeness Stages

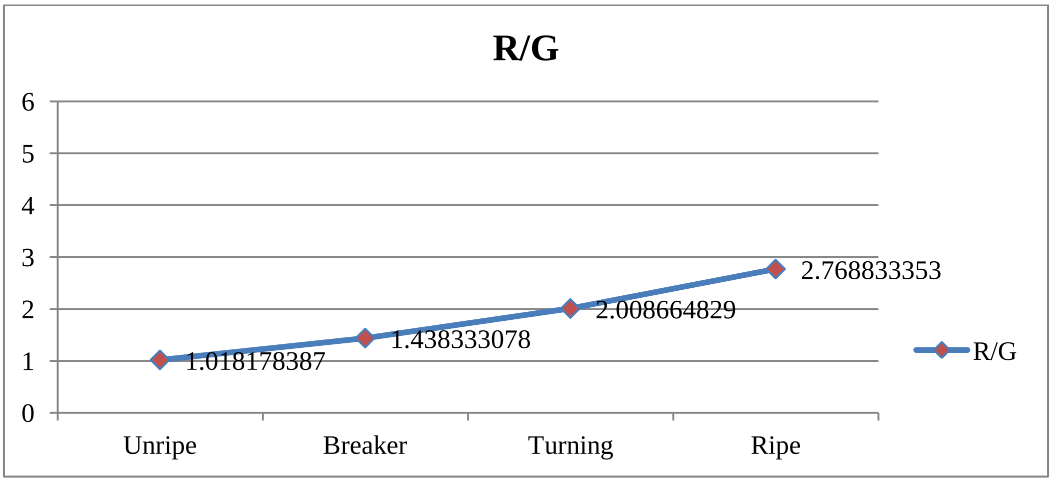


Figure 5.3: Behavior of Average R/G Values of the Images for Four Classes

Table 5.1: Average R, G and B Component Values of the Images for Four Classes

Classes	AvgR	AvgG	avgB
Unripe	161.87	158.98	55.65
Breaker	187.76	130.54	44.65
Turning	204	101.56	37.5
Ripe	230.45	83.23	28.34

Table 5.2: Red-Green Difference, Red-Green Ratio Values of the Images for Four Classes

Classes	R-G	R/G
Unripe	2.89	1.01
Breaker	57.22	1.43
Turning	102.44	2.00
Ripe	147.22	2.76

Table 5.1 shows the average red, green and blue values of all the images for each of the four classes of ripeness. Table 5.2 shows the values of R-G and R/G of all the images for each of the four classes. Both R/G and R-G shows the linear behavior as the level of maturity increases. The performance of both the color depictions have been compared for different classification technique to find out that which of the two color depictions is more suitable to achieve better classification results of maturity phase for the proposed techniques. Three classification techniques namely KNN, SVM and Decision Tree are used to compare the two color depictions R/G and R-G. Hundred runs have been executed for each of the algorithms for both the color depictions. The test and train data are randomized keeping the same percentage split for each run.

The classification accuracy is calculated for both R-G and R/G for all the three classification techniques. Classification accuracy can be defined as the percentage of correctly classified images out of a total number of testing images considered. Average of the classification values obtained for total runs is calculated and depicted. Figure 5.4 shows the classification accuracy for fruit ripeness obtained by applying three algorithms. Figure 5.4 depicts that classification accuracy for R-G is higher than that for R/G for all three algorithms. The significant output is that R-G is capable of classifying images better than that R/G for any algorithm. Therefore, R-G is selected as the color depiction feature for the proposed APRE technique.

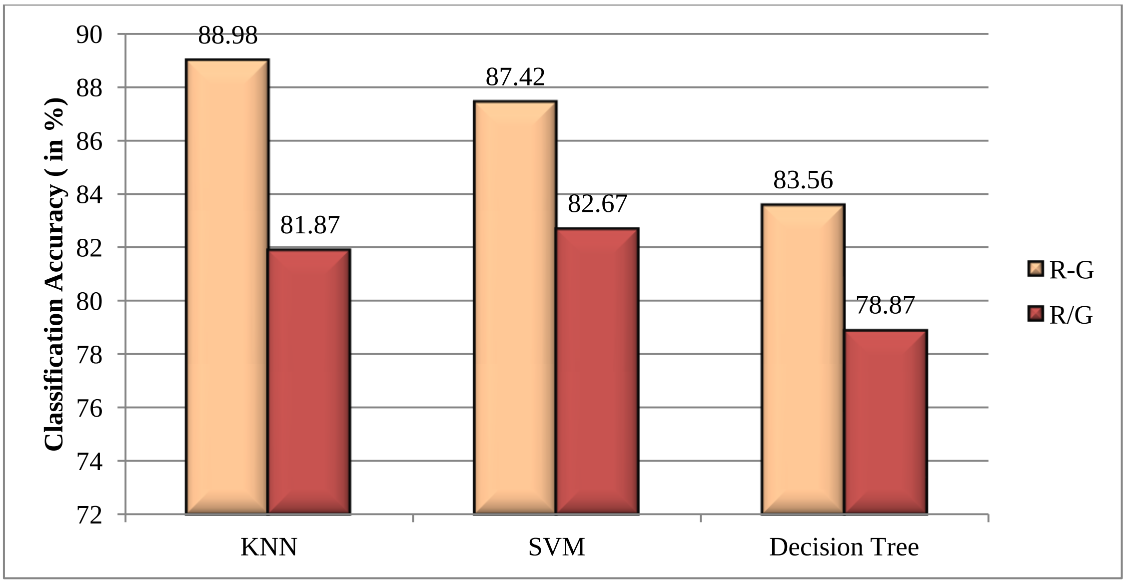


Figure 5.4: Classification Accuracy of R-G and R/G for Different Algorithms

5.2 Metrics Used for Performance Evaluation

The proposed techniques APRE and FRRE have been compared with the existing K-NN, SVM and Decision Tree classification techniques. Here TP, FP, TN and FN are the numbers of the true positive, false positive, true negative and the false negative predictions for the considered class, respectively[65]. The following metrics have been considered for the proposed APRE and FRRE techniques:

a. **False Positive (FP) rate:** FP Rate is the proportion of images which have been classified as class 'X', but they belong to a different class, among all images which are not of class 'X' as given by Equation (5.1):

$$FP\ Rate = \frac{FP}{FP + TN} \tag{5.1}$$

b. **Precision:** It is the proportion of the images which truly have class 'X' among all those which have been classified as class 'X'. On the other hand, precision is defined as the proportion of the predicted positive classes which are correctly identified as given by Equation (5.2):

$$Precision = \frac{TP}{TP + FP} \tag{5.2}$$

Here, TP Rate is the proportion of images which have been classified as class X, among all images which truly have class x. It is equivalent to Recall.

c. **Sensitivity:** It is the proportion of the actual positive classes which are correctly identified as given by Equation (5.3). Sensitivity is defined as the ability of the prediction model to select the instance of a certain class from the dataset.

$$Sensitivity = \frac{TP}{TP + FN} \tag{5.3}$$

d. **F-Measure:** It is simply a combined measure for precision and recall as given by Equation (5.4):

$$Fmeasure = \frac{2 \times Precision \ \times Recall}{Precision + Recall} \tag{5.4}$$

e. **Specificity:** It is defined as the proportion of actual negative classes which are correctly identified as given by Equation (5.5):

$$Specificity = \frac{TN}{TN + FP} \tag{5.5}$$

f. **Overall Class Prediction Accuracy:** It is defined as the proportion of the total number of predictions which are correct as given by following equation:

$$Overall\ Predicted\ Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5.6}$$

Overall class prediction accuracy and Specificity are the useful statistical measures which analyzes the performance of a classifier.

5.3 Performance Evaluation

The dataset which has been considered for the performance evaluation consists of 2832 images. Table 5.3 shows the blend of the dataset which has been considered.

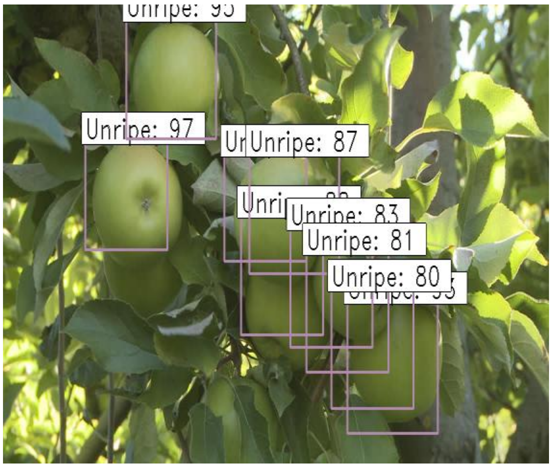
Initially, there was only 602 number of images, so Augmenter tool[66] has been used to generate the large dataset by performing various operations such as scaling, rotation and transformation, etc. 70 % of the data set has been used for training and 30% of the dataset has been considered for testing. So, the number of instances considered for testing based on the table is 164, 220, 201 and 265 for Unripe, Breaker, Turning and Ripe classes respectively.

Table 5.3: Number of Images Considered for Each Ripeness Stage

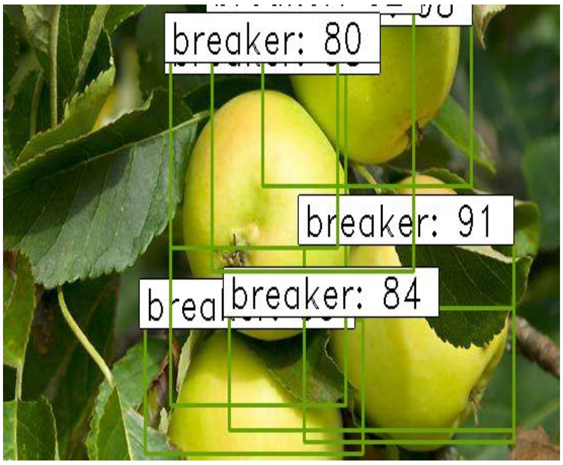
Ripeness Stage	Number of Images
Unripe	546
Breaker	734
Turning	670
Ripe	882

The proposed APRE and FRRE techniques have been compared with the existing techniques such as Decision Tree, KNN and SVM in terms of FP Rate, Precision, Specificity, F-Measure, Sensitivity and Accuracy. Results obtained for performance evaluation and comparison are listed in Tables 5.4 – 5.10. Figure 5.5 shows the results obtained by the proposed FRRE technique.

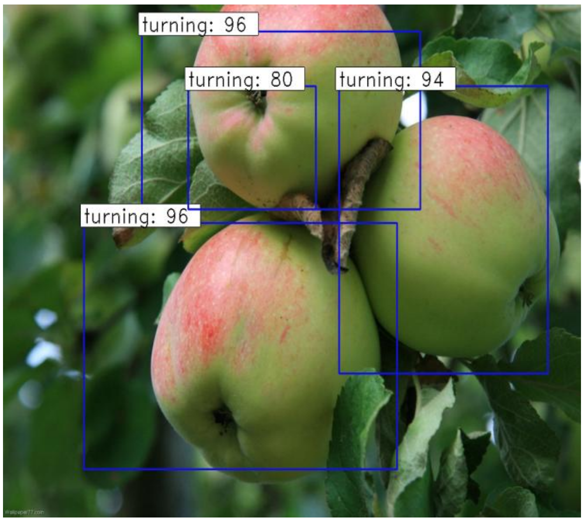
Figure 5.6 depicts the FP Rate results obtained for the proposed APRE and FRRE techniques and results are also compared with the existing techniques. The values shown in Figure 5.6 have been calculated based on Equation (5.1). The value of the FP rate lies between 0 and 1. The FP rate of proposed FRRE is minimum i.e. 0.01. It means only 1% of total instances have been misclassified as positive. For instance, an input is classified as Ripe, but in actual it is not ripe. The proposed APRE technique also performs efficiently as compared to the existing techniques with an FP rate of only 0.04. The reason behind the difference in FP rate of the proposed techniques is that APRE misclassified few turning class image as Ripe class image.



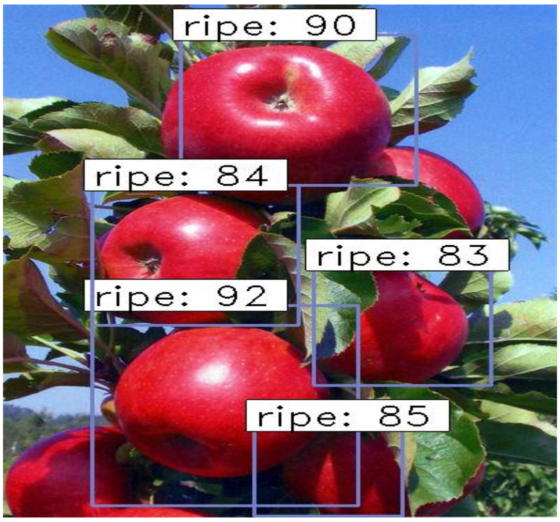
(a) Unripe



(b) Breaker



(c) Turning



(d) Ripe

Figure 5.5: Ripeness Stages Classified by Proposed FRRE Technique

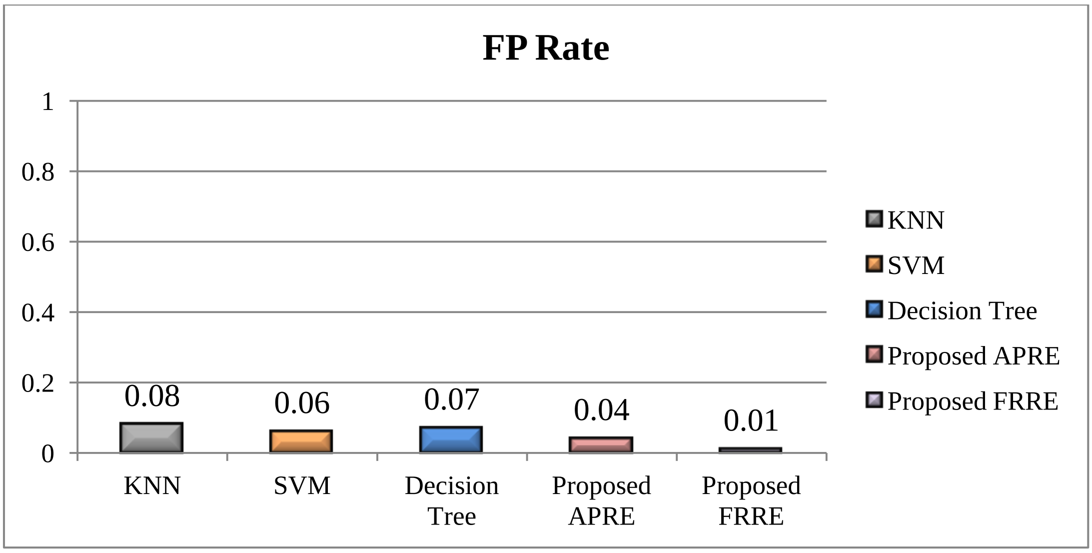


Figure 5.6: Comparative Analysis of FP Rate

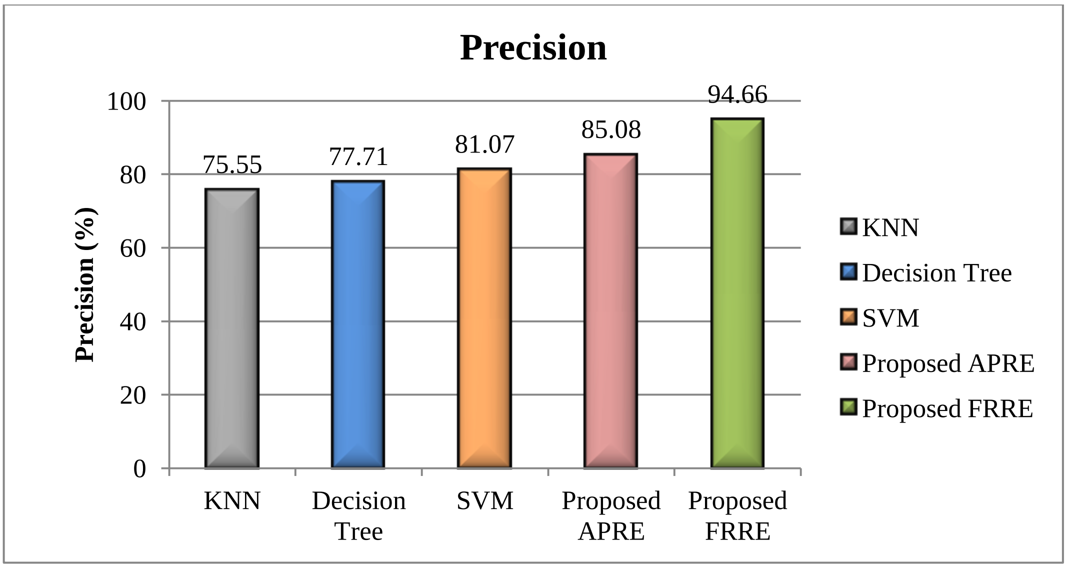


Figure 5.7: Comparative Analysis of Various Techniques in Terms of Precision

Figure 5.7 depicts the precision results obtained for the proposed APRE and FRRE techniques and results are also compared with the existing techniques. The values shown in Figure 5.7 have been calculated based on Equation (5.2). Here, the value of precision is calculated in percentage. Its values lie between 0 and 100%. The precision of proposed FRRE is maximum i.e. 94.66%. It means if the proposed technique classifies an input as X, then there are chances that 94.66% of the time, it will be correct. The proposed APRE technique also performs efficiently as compared to the existing techniques with an FP rate of 85.08%. The minimum precision is reported by KNN in this scenario.

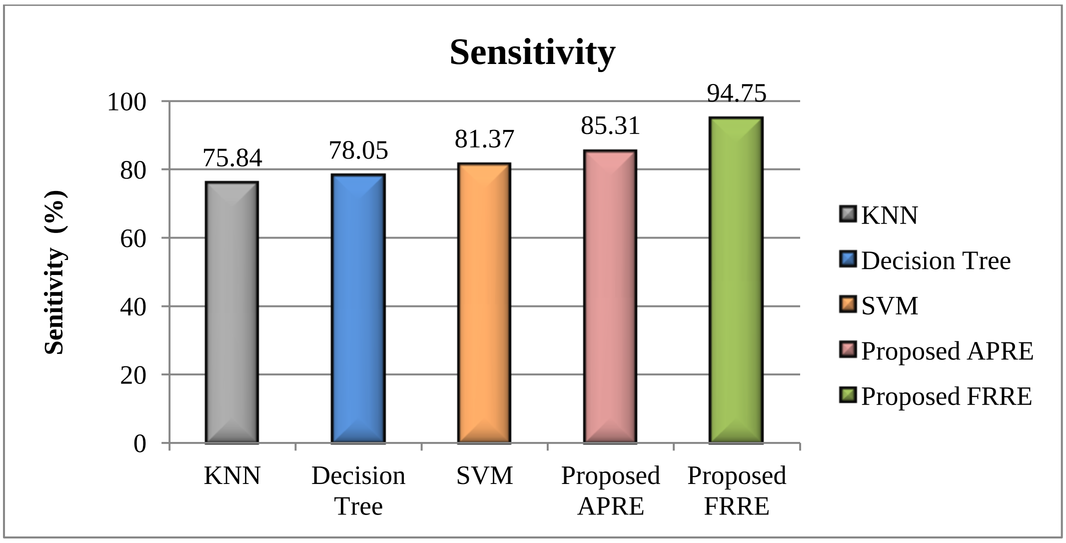


Figure 5.8: Comparative Analysis of Sensitivity

Figure 5.8 depicts the sensitivity results obtained for the proposed APRE and FRRE techniques and results are also compared with the existing techniques. The values shown in Figure 5.8 have been calculated based on Equation (5.3). Here, the value of precision is calculated in percentage. Sensitivity measures the proportion of actual positives that are correctly identified as such (e.g., the percentage of ripe fruits who are correctly identified as ripe). The sensitivity of proposed FRRE is maximum i.e. 94.75%. The proposed APRE technique also performs efficiently with a sensitivity of 85.31%. and performs significantly better as compared to the existing techniques.

F-measure is calculated based on precision and recall. It defines the overall performance of the technique which has been considered. Figure 5.9 depicts the score of F-measure results obtained for the proposed APRE and FRRE techniques and are compared with the existing techniques. The values shown in Figure 5.9 have been calculated based on Equation (5.4). Here, the value of F-Measure is calculated in percentage. F-score or F-measure of proposed FRRE and APRE techniques are 94.71% and 85.18% respectively. Both proposed techniques perform significantly better as compared to the existing techniques in terms of F-Measure. These values indicate the good classification capability of the proposed techniques.

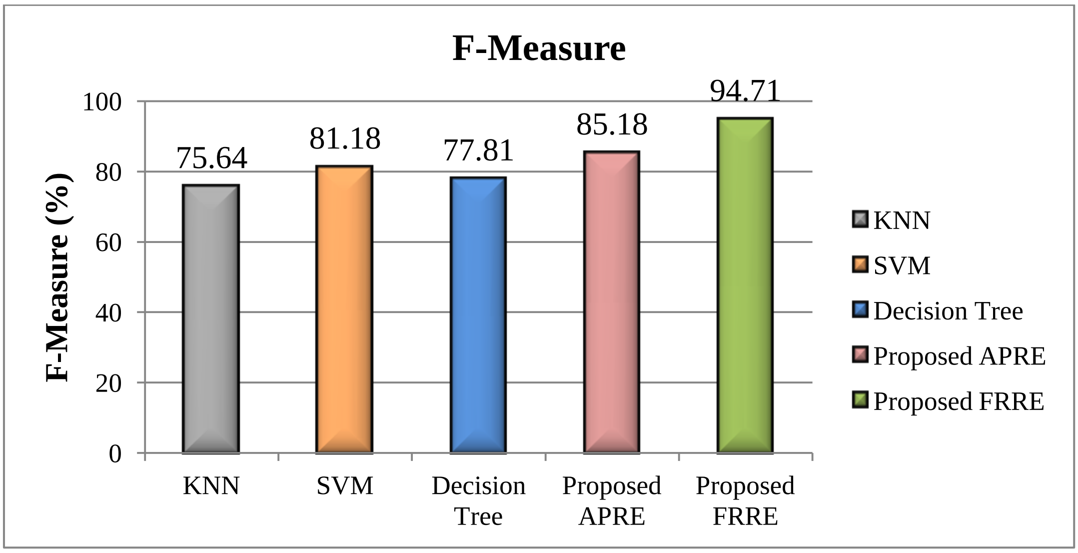


Figure 5.9: Comparative Analysis of F-Measure

Figure 5.10 depicts the score of specificity results obtained for the proposed APRE and FRRE techniques. The results have been compared with the existing techniques. The specificity of a test is its ability to designate a fruit who is not ripe as negative. Highly specific results mean that there are few false positive results. The values shown in Figure 5.10 have been calculated based on Equation (5.5). Here, the value of specificity is calculated in percentage. The specificity of proposed FRRE and APRE techniques are 98.1% and 95.18% respectively. Both the proposed techniques perform significantly better as compared to the existing techniques in terms of specificity.

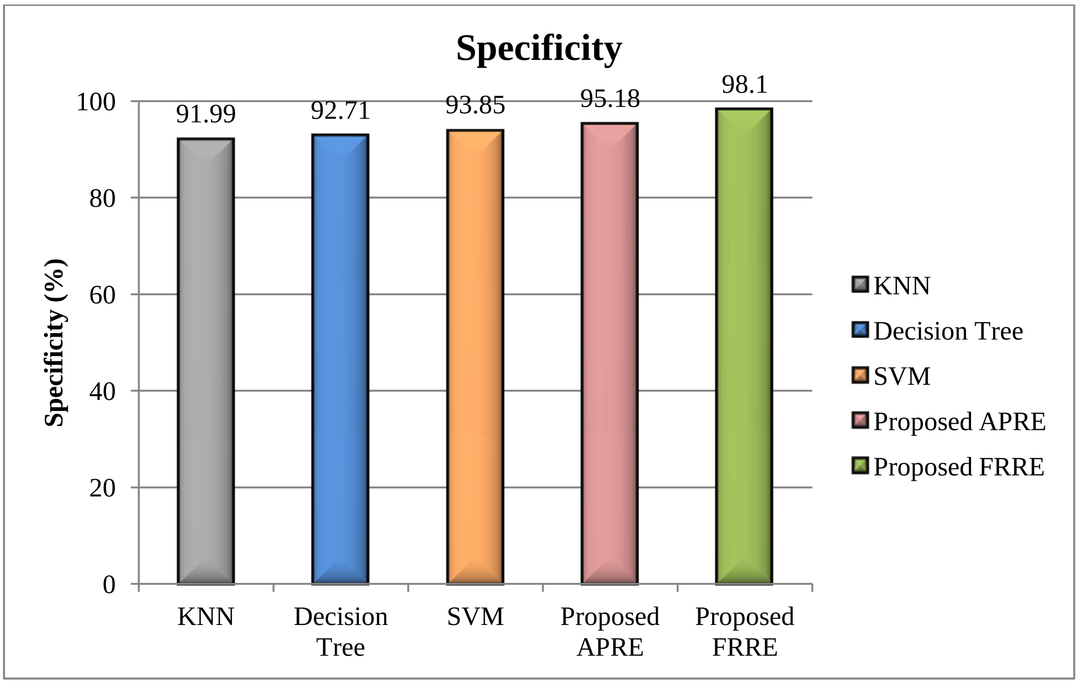


Figure 5.10: Comparative Analysis of Specificity

Tables 5.4, 5.5, 5.6, 5.7 and 5.8 show the confusion matrices for the proposed FRRE and APRE techniques along with existing SVM, Decision Tree and KNN classification techniques. The simulation results have been compared and it can be concluded that the overall correctness or the model classification accuracy and the class sensitivity of the SVM, Decision Tree and KNN are less than the proposed APRE and FRRE techniques. The overall correctness reported by the proposed APRE, FRRE and existing techniques KNN, SVM and Decision Tree is 85.19%, 94.7%, 75.85%, 80.84% and 77.87% respectively. The proposed FRRE technique performs better than the proposed APRE technique.

Table 5.4: Confusion Matrix for the Proposed FRRE

Actual Class	Predicted Class				
	Unripe	Breaker	Turning	Ripe	Class Sensitivity
Unripe	152	12	0	0	92.68
Breaker	13	207	0	0	94.09
Turning	0	0	193	8	96.01
Ripe	0	0	10	255	96.22
Class Precision %	92.12	94.52	95.07	96.95	Overall Correctness = 94.7%

Table 5.5: Confusion Matrix for the Proposed APRE

Actual Class	Predicted Class				
	Unripe	Breaker	Turning	Ripe	Class Sensitivity
Unripe	137	27	0	0	83.03
Breaker	33	187	0	0	85
Turning	0	0	173	28	86.06
Ripe	0	0	34	231	87.16
Precision %	80.58	86.97	83.57	89.18	Overall Correctness =85.19%

Table 5.6: Confusion Matrix for SVM

Actual Class	Predicted Class				
	Unripe	Breaker	Turning	Ripe	Class Sensitivity
Unripe	131	33	0	0	80.6
Breaker	41	178	0	0	81.36
Turning	0	0	165	36	82.08
Ripe	0	0	46	219	82.64
Precision %	71.97	84.03	78.19	85.88	Overall Correctness =80.84%

Table 5.7: Confusion Matrix for Decision Tree

Actual Class	Predicted Class				
	Unripe	**Breaker**	**Turning**	**Ripe**	**Class Sensitivity**
Unripe	126	38	0	0	76.36
Breaker	47	173	0	0	78.63
Turning	0	0	159	42	79.1
Ripe	0	0	58	207	78.11
Precision %	72.83	81.6	73.27	83.13	Overall Correctness = 77.87%

Table 5.8: Confusion Matrix for KNN

Actual Class	Predicted Class				
	Unripe	**Breaker**	**Turning**	**Ripe**	**Class Sensitivity**
Unripe	121	43	0	0	73.33
Breaker	50	170	0	0	77.27
Turning	0	0	153	48	76.11
Ripe	0	0	63	202	76.22
Precision %	70.76	79.81	70.83	80.8	Overall Correctness= 75.85%

The detailed binary confusion matrix of proposed APRE and FRRE techniques have been presented in Table 5.9 and 5.10 respectively. The detailed analysis of TP, TN, FN, FP, Sensitivity, Precision, Specificity and overall accuracy of the proposed APRE and FRRE techniques has been presented in these tables.

Table 5.9: Binary Confusion Matrix for the Proposed FRRE Technique

Actual Class	**Predicted Class**		
	Unripe	**Not Unripe**	
Unripe	TP=152	FN=12	Sensitivity=92.68
Not Unripe	FP=13	TN=673	Specificity=98.10
(In %)	Precision=92.12	Negative predictive value=98.24	Overall accuracy=97.05
	Breaker	**Not Breaker**	
Breaker	TP=207	FN=13	Sensitivity=94.09
Not Breaker	FP=12	TN=618	Specificity=98.09
(In %)	Precision=94.52	Negative predictive value=97.93	Overall accuracy=97.05
	Turning	**Not Turning**	
Turning	TP=193	FN=8	Sensitivity=96.01
Not Turning	FP=10	TN=639	Specificity=98.45
(In %)	Precision=95.07	Negative predictive value=98.76	Overall accuracy=97.88
	Ripe	**Not Ripe**	
Ripe	TP=255	FN=10	Sensitivity=96.22
Not Ripe	FP=8	TN=577	Specificity=98.63
(In %)	Precision=96.96	Negative predictive value=98.26	Overall accuracy=97.88

Table 5.10: Binary Confusion Matrix for the Proposed APRE Technique

Actual Class	**Predicted Class**		
	Unripe	**Not Unripe**	
Unripe	TP=137	FN=28	Sensitivity=87.03
Not Unripe	FP=33	TN=653	Specificity=95.18
(In %)	Precision=80.58	Negative predictive value=98.38	Overall accuracy=92.83
	Breaker	**Not Breaker**	
Breaker	TP=187	FN=33	Sensitivity=85
Not Breaker	FP=28	TN=603	Specificity=98.25
(In %)	Precision=86.97	Negative predictive value=94.81	Overall accuracy=92.83
	Turning	**Not Turning**	
Turning	TP=173	FN=28	Sensitivity=86.06
Not Turning	FP=34	TN=616	Specificity=94.76
(In %)	Precision=83.57	Negative predictive value=95.65	Overall accuracy=92.71
	Ripe	**Not Ripe**	
Ripe	TP=231	FN=34	Sensitivity=87.16
Not Ripe	FP=28	TN=558	Specificity=95.22
(In %)	Precision=89.18	Negative predictive value=94.25	Overall accuracy=92.71

Figure 5.11 displays the detailed accuracy for each of the four classes for the proposed FRRE and APRE techniques. The results have been calculated based on Equation (5.6). The performance of the proposed FRRE and APRE techniques have been compared with the existing techniques KNN, SVM and Decision Tree. It can be concluded that KNN and proposed FRRE techniques report the minimum and maximum accuracy respectively. The proposed FRRE technique performs 4.69%, 9.39%, 7.69% and 15.13% better than APRE, Decision Tree, KNN and SVM techniques respectively in terms of accuracy. The proposed APRE technique also

performs 4.7%, 10.44% and 3% better as compared to the existing techniques such as Decision Tree, KNN and SVM in terms of accuracy.

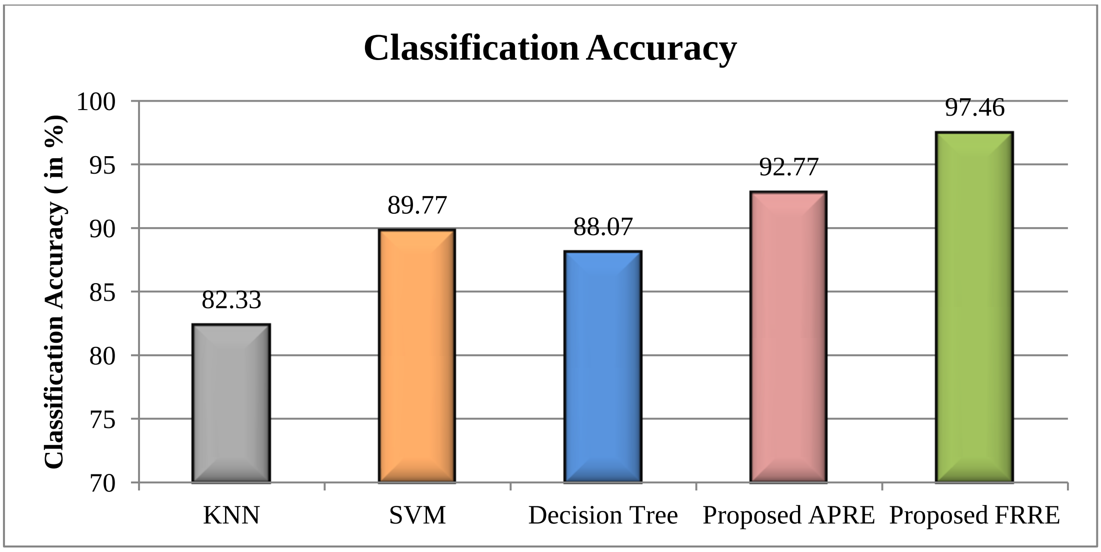


Figure 5.11: Comparative Analysis of Classification Accuracy

Hence, the proposed FRRE is better than the proposed APRE technique in distinguishing between the “right” class and “not the right” class. The reason for this is that images whose true class is breaker have been incorrectly classified into the unripe stage. The same can be seen in the confusion matrix in case of turning and ripe classes. This error results in dropout in precision and F-measure for both the ripe and turning classes. Hence, the FRRE technique is better than the APRE technique in distinguishing between the various classes. The FRRE has a perfect measure of separability between classes as compared to the other techniques.

Chapter 6
CONCLUSION AND FUTURE SCOPE

6.1 Conclusion

Through this research, we intend to focus on understanding the various ripeness stages of fruits and conduct ripeness estimation of fruits via various techniques.

- The problem stated in Section 3 has been solved as elucidated in Sections 4 and 5. Two techniques have been proposed namely efficient *ANFIS based Pre-harvest Ripeness Estimation (APRE)* and *Faster R-CNN based Ripeness Estimation* (FRRE) technique in Section 4.1 and 4.2 respectively.
- In the proposed *APRE* technique, ANFIS has been utilized to classify the fruits into four ripeness stages. Initially, various data analysis and processing steps have been performed on the data set such as pre-processing and segmentation. Two color depictions have been considered: R-G and R/G. Based on comparative analysis in terms of accuracy, it has been concluded that R-G depictions are better to choose in the proposed methodology.
- In the proposed FRRE technique, *Faster R-CNN* has been utilized to classify the fruits into four ripeness stages. In this technique, probable bounding boxes are generated in which there are chances of the existence of the object of interest and then the input image is classified into the appropriate ripeness class.
- The performance of the proposed APRE and FRRE techniques has been compared with the existing techniques in terms of FP Rate, Sensitivity, Specificity, F-Measure, Precision and accuracy. The proposed FRRE technique performs 4.69%, 9.39%, 7.69% and 15.13% better than APRE, Decision Tree, KNN and SVM techniques respectively in terms of accuracy. The proposed APRE technique also performs 4.7%, 10.44% and 3% better as compared to the existing techniques such as Decision Tree, KNN and SVM in terms of accuracy.

6.2 Summary of Contributions

The proposed techniques can be utilized to other classification fields as well other than ripeness classification. It can be utilized while exporting the crops, as it can be utilzed for selecting the optimal ripeness stage. The climatic fruits can be picked at an early stage of ripeness for long-distance transportation, while these can be picked up at later stages of ripeness for short distance. The proposed techniques can also be utilized to automate the estimation of ripeness process for other climatic fruits and vegetables. Two techniques have been proposed namely efficient *ANFIS based Pre-harvest Ripeness Estimation (APRE)* and *Faster R-CNN based Ripeness Estimation* (FRRE) technique.

Following are the main contributions of the APRE technique:

- In the work presented, the images of fruits are collected. These images are based on four different maturity stages. Fruits are segmented from the captured images under natural complicated background while at the same time the color integrity of the image is also maintained.
- Red-green color difference has been used as the feature space as it tends to increase progressively with the increase in the ripeness of fruit. A detailed analysis of different color feature representations (averages of R, G and B, R-G and R/G) has been done. It is shown that red-green color difference has the good classification capability as compared to the individual components R, G, B or red-green ratio in RGB color space.
- A fuzzy rule-based classification system based on ANFIS is used to classify the fruits into four maturity stages based on Red-green color difference.
- The work presented provides the self-sufficient decision-making means for the harvesting without the need of any human expert.

Following are the main contributions of the FRRE technique:

- First, is to develop an efficient pre-harvest ripeness estimation technique for fruits which can be trained with a small dataset quickly. DCNN is pre-trained based on a large dataset such as ImageNet and PASCAL VOC [51].
- Second Faster R-CNN along with RPN is utilized to determine the ripeness stage of the fruit. RPN can determine the probable bounding boxes of a fruit

and can help to segment the required fruit from its background. The proposed technique provides an optimal approach to identify the fruits and there ripeness stage based on an input image.

6.3 Future Scope

Though some challenges still need to overcome, machine vision will prove to be the future for non-destructive fruit classification and grading. In the future, work can be done on image classification for local fruits and vegetables. The algorithms and machines can be designed for fruits and vegetable grading. Some more features can be considered for grading and classification, which can identify types of disease and texture structure of fruits. A prototype model can be developed, which can be used in industries. A mobile application can be developed for the same based on the above methods. Farmers or the general public can use it for identification, classification, and grading of horticultural products. Future work will involve proposing techniques to recognize unknown fruit classes and sub-classes as well as recognizing known fruit classes/sub-classes within a collection of multiple fruits. From the viewpoint of utilized approach in the proposed system, some more future research directions can be considered. External features other than colors such as shape, size and texture can be involved in the classification of fruit. This will help in better quality evaluation. Fruit counting is also one of our future works. This task includes data association, which means we need to distinguish whether fruit is already seen from the previous image frame or not. Feature matching, tracking and association techniques are required to identify fruits.

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LIST OF PUBLICATIONS

- Shubhdeep Kaur, Sushma Jain and Avleen Malhi, "A Review on Ripeness Prediction Approaches for Fruits", *International Conference on ICT for Sustainable Development (ICT4SD)*, Springer, Goa, 2019. **[Accepted and to be published].**
- Shubhdeep Kaur, Sushma Jain and Avleen Malhi, "A Review on Disease Detection and Classification of Fruits", *International Conference on Trends in Electronics and Informatics*, IEEE, Tirunelveli, Tamil Nadu, 2019. **[Presented and to be published].**
- Shubhdeep Kaur, Sushma Jain and Avleen Malhi, "An efficient Pre-Harvest Technique for Fruits" *Journal of Food Science and Technology* **[Communicated].**

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