QUALITY ASSESSMENT OF BLACK TEA BASED ON PHYSICAL PARAMETERS USING MACHINE VISION

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by

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CERTIFICATE

I hereby certify that the work which is being presented in the thesis entitled, "Quality Assessment of Black Tea Based on Physical Parameters using Machine Vision", for the award of degree of Doctor of Philosophy in Electrical and Instrumentation Engineering Department (EIED), Thapar University, Patiala, is an authentic record of my own work carried out under the supervision and guidance of Dr. Ravinder Agarwal, Professor, EIED, Thapar University, Patiala and Dr. Amod Kumar, Chief Scientist, CSIR-CSIO, Chandigarh.

The matter presented in this thesis has not been submitted either in part or in full to any university or institute for award of any degree.

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ABSTRACT

Tea is a valuable cash crop throughout the world. It is a major export product of India. As far as social aspect is concerned, about 1.2 million people are directly employed as labour in tea industry. This constitutes a large proportion of human resource of the country. Quality of tea plays a significant role in its marketability as international export price of tea is fixed according to its quality. At present, tea quality is validated by professional ‘Tea Tasters’ who charge exorbitantly for every sip they take. Conventionally, these experts evaluate tea quality by use of organoleptic methods during fermentation and sorting stage. In addition to this, gas chromatography and colorimetery are employed for chemical analysis of tea liquor and for colour analysis, respectively, at various stages of tea processing. These conventional methods have many shortcomings. First of all, being small in number, the Tea Tasters are difficult to hire and there is every possibility of formation of a cartel by them. Their evaluation methods are subjective and suffer from high labour costs, inconsistency and variability. The prominent physical parameters that establish tea quality include colour, texture, grain shape and size. The approach of Tea Tasters does not quantify these parameters and hence, it is difficult to correlate various parameters of tea for assessment of tea quality. Increasing competition and concerns about tea quality leading to rejection of export orders has resulted in substantial fall in tea export from India in the recent past and consequently, tea industry of India is slowly dying. If proper measures are not adopted and lessons not learnt from the past, situation may aggravate in future. There is a dire need to carry out research in this field so as to meet requirements of global standards. There has been lack of research specifically related to grading and quality assessment of tea all over the world.

The above issues are aptly addressed by machine vision based techniques. This work documents the efforts carried out for objective grade assessment of tea quality at the post processing stage with the application of machine vision techniques. In addition to estimation of colour, shape, size and texture by machine vision, direct measurement of two prominent physical parameters namely, moisture and density has been carried out for quality assessment. The present work was taken up to carry out research in this field which has very high socio-economic significance not only for India but for all tea exporting South Asian countries. The main issues required to be addressed by this work include:

- Determination of size, shape, texture, etc. of granules of tea non-destructively by machine vision for assessment of tea grade.
- Determination of colour of brewed tea liquor for assessment of grade.
- Measurement of moisture and density of various grades of tea for grade discrimination.
- Development of a classifier followed by statistical validation of results.

The problems addressed through machine vision technique have certain definite steps to be followed in sequence with image acquisition followed by image pre-processing, feature extraction. Finally, extracted features are classified. Image acquisition is greatly affected by factors such as selection of camera, viewing distance, orientation of illumination source etc. Due care has be taken at this stage to ensure efficient capturing of image data with a high degree of fidelity. Another critical aspect is feature extraction which involves identification and estimation of suitable features that describe the data uniquely. Towards the end, the classification stage deals with selection of appropriate classifier for classification of feature data. In the present work, as a first step, an objective discrimination amongst the various tea grades of tea was carried out on the basis of their morphological features *viz.* area, perimeter and aspect ratio. The results were compared with the standard samples obtained from tea industry which were duly graded by tea tasters. Finally, with the extracted features when presented to the three inputs MLP, a grading accuracy of 100% was achieved. Statistical analysis by ANOVA (Analysis of Variance) highlighted area and perimeter as key attributes for discrimination between various grades. Further, the possibility of discriminating various grades of tea granules on the basis of their texture was explored. In the present work, four diverse grades of black tea are discriminated using between using textural features on the basis of spatial location of their grey shade intensities. Certain statistical attributes like energy, entropy, contrast, correlation and homogeneity are evaluated for the image database comprising of images of diverse grades. When these features are classified using MLP, an accuracy of 87.5% was achieved. Further, upon decomposition into sub-band images by DWT, the same features were computed and an improved accuracy of 100% was observed. In the next stage, colour estimation was carried out for discriminating the different grades on the basis of colour of tea liquor. Grade assignment was done on the basis of extracted colour features using the RGB colour model and 100% accuracy was observed using MLP classifier.

Another prominent parameter that determines the shelf life and storage quality of black tea i.e. moisture has been investigated for different grades of tea. It has been observed that the moisture retention is more in the grades having larger granules than the grades having smaller granule sizes. Finally, compacted and un-compacted densities were measured for various tea grades and it has been observed that the density enjoys an inverse relation with the granule size.

It is worth mentioning here that the procedures carried out in the present work for quality assessment, except colour analysis, are predominantly non-invasive in nature. If a system is developed using the proposed concept, it is expected that it can successfully assist the traditional methods in the tea industries for quality assessment and monitoring.

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LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
ANOVA	Analysis of Variance
AR	Auto Regressive
CCD	Charged Coupled Device
CMY(K)	Cyan Magenta Yellow (Key)
CTC	Cutting Tearing Curling
DPI	Dots Per Inch
DWT	Discrete Wavelet Transform
FL	Fuzzy Logic
GA	Genetic Algorithm
GDM	Gradient Descent with Momentum
GLCM	Grey Level Co-occurrence Matrix
GOI	Government of India
GRF	Gibbs Random Field
HSI	Hue Saturation Intensity
LBP	Local Binary Pattern
LM	Levenberg-Marquardt
LOG	Laplacian-of-Gaussian
MLP	Multi Layer Perceptron
MRF	Markov Random Field
MSE	Mean Square Error
PDF	Probability Distribution Function
PNN	Probabilistic Neural Network

RGB	Red Green Blue
STFT	Short Term Fourier Transform
TF	Theaflavin
TR	Thearubigin
TGA	Thermo Gravimetric Analysis
WHO	World Health Organization
WFT	Windowed Fourier Transform
YIQ	Luminance In-phase Quadrature

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION

Tea is a popular beverage throughout the world. Globally, people prefer to have a cup of tea for relieving stress or, just, for the sake of pleasure. Nearly, half of the world's population consumes tea. The production and trade of tea has become an important business for centuries. In 1990, the tea growing area in the world reached 2.45 million hectares with total yield of 2.51 million tons. India is the largest producer, with a total production of tea approaching one million tonnes in 2013-14 and exports of 2,49,900 metric tons (GOI, 2015). India is also a major exporter of tea globally having export share of 4873 crores in the year 2013-14 (GOI, 2015). World tea consumption has increased steadily over the years. Over 3 billion cups of tea are consumed, globally, on daily basis. Black tea is preferred by majority of consumers (more than 75%) followed by other types of tea. Factors considered by consumers for selection of a particular type of tea are its availability, taste, cost, and noticeable health benefits (Bhattacharya *et.al.*, 2014). Because of the high popularity of tea, the relationship between tea and health has come out as one of the most attractive topics in biomedical sciences (Jain *et. al.*, 1999; Chen, 2005).

The increasing incomes and awareness, growing number of consumers giving high priorities to food quality in addition to increasing exports of agricultural produce have emerged as vital factors for growing concern for quality assessment of raw and processed agricultural produce after Green Revolution in India. The same applies to tea, as well, and tea industry in India needs to pay increased attention to quality of its produce because of growing trade competitiveness. Weaknesses in quality assessment and grading systems can cost high to tea industry and the economy of the country.

The grading system for agricultural products ensures enhanced marketability and a better price to the producer by fixing up rates on the basis of quality. Recognizing this need, the Indian government introduced the procedures to standardise of agro-produce so as to ensure that maximum benefits of grading are passed on to the farming community as per the Agricultural Produce Grading and Marking Act which came into force in 1937. The standards for grading set according to this act are adopted after critical analysis of crop samples of each crop, taken from diverse zones of production and cultivated in different climatic conditions. In addition to this, the global standards and particular wants and expectations of global clients should also be considered before drafting and amending such standards for the agro-products that are exported. These grades are designated as the 'Agmark' grades.

In the past, India suffered massive setbacks due to stiff competition in the international market as various consignments of agricultural produce from India were rejected on the basis of poor quality. For instance, a 16-million kg tea market, Libya, imposed a five year ban on tea imports in protest against the export of three million kg of ‘substandard tea’ from India in 1998-99, and in the following years Libya started importing tea from Sri Lanka (Bose, 2004). In 2001, Iraq rejected two consignments of 23,500 tons of wheat shipments from the country on grounds of bad quality and the order was subsequently bagged by Pakistan (Chandrasekhar, 2001; Shahzad, 2001). India's share in the world exports for tea has dropped from 33.4% in 1970 to 10.5% in 2013. India as a growing economy can’t afford to lose its export orders for the cash crop like tea for which it is the world leader in production and exports. India strongly needs indigenously developed modern and sophisticated techniques for quality assessment of agricultural produce in order to withstand the global competition. The issue assumes appreciable importance as the problem regarding absence of suitable grading systems for quality evaluation and classification to meet the quality requirements of consumers in domestic and export market was also stressed in Issue 8 of the Report on Food and Agro Industries Management Policy by Prime Minister’s Council of Trade and Industry (Wadia, 1998)

1.2 MOTIVATION AND OBJECTIVES

In the present work, an effort is done for developing a machine vision system to access quality of black tea. The work has been carried out with an orientation towards tea for the following reasons:

- Tea is viewed as a valuable cash crop, globally. It’s a major cash crop of India and in the recent past owing to poor grading techniques, the tea exports have been gradually declining and, consequently, tea industry of India is slowly dying.

- As far as social aspect is concerned, 12,59,500 people are directly employed as labor in tea industry (Vinayakumar, 2011). This constitutes a large proportion of human resource of the country.
- International export price of tea is fixed according to its quality. At present, this quality is validated by professional tea tasters who charge exorbitantly for every sip they take. Being small in number, these tea tasters are difficult to hire. Secondly, this method of quality assessment is subjective.
- Lack of research in this area of non invasive quality assessment of tea

It is evident that increasing competition and concerns about tea quality leading to rejection of export orders may result in substantial fall in tea export from India in future. There is a dire need to carry out research in this field in order to meet requirements of international standards. There has been lack of research specifically related to grading and quality assessment of tea all over the world. The present research in this field has very high socio-economic significance not only for India but for all tea exporting South Asian countries.

The primary objective of my research is to investigate the potential of machine vision based approach for tea quality assessment by taking into consideration various physical attributes such as shape, size texture, colour, moisture, density, etc. at post processing grading stage.

1.3 ORGANIZATION OF THE THESIS

Following this introductory chapter, which explains the motivation behind the present work as well as the objectives of the research, Chapter 2 presents the work of researchers till date. Various stages of production of tea are explained here along with the tea chemistry. The applications of machine vision in food industry have been discussed. Finally, the soft computing based techniques have been described as the suitable classification techniques for such problems.

Chapter 3 focuses more closely on the methodology adopted for the current research. The methods and materials have been discussed citing suitable reasons for choosing the specific approach. Algorithms have been developed for grading of tea on the basis of shape and size, texture, colour, density and moisture. Statistical methods have been employed for feature analysis which serves as a validation tool for the results obtained from the classifier.

Chapter 4 presents a discussion of the results obtained.

Chapter 5 presents quality assessment of tea and prospective use of more sophisticated methods as future works.

CHAPTER 2

REVIEW OF LITERATURE

The term 'tea quality' is associated with the overall quality of tea which is a predefined standard. It is dependent on various aspects, namely, tea cultivation and harvest, environment conditions, post harvest processing techniques, etc. These attributes need to be controlled to obtain a preferred quality. In the present scenario, the ever increasing consumer base concerned about the quality aspects pushes the requirement for a precise quality estimation of tea. Improving tea quality has come up as a serious concern for tea industry. Conventional methods of tea quality assessment are non-standardized and need an improvisation. Machine vision based techniques are of great help in addressing these existing issues associated with tea quality estimation. These methods are advantageous in handling the concerns encountered with long-established human sensory panel judgmental methods which inherently suffer from factors such as human variability, insensitivity due to prolonged exposure and mental status. The rationale of the chapter is to discuss the essential background pertinent to this research.

2.1 TEA QUALITY ASSESSMENT

Assessment of quality of tea is a multifarious phenomenon and there are no particular terms to describe overall quality of tea. It may also vary according to choice of diverse individuals. The tea tasters follow certain terminology to explain the quality. At present, two approaches are being followed for quality indexing tea industry. While one involves the evaluation of biochemical indicators of tea either at fermentation stage of or post-production stage, the other one is a purely subjective method involving subjective judgment through professional tea tasters. The subjective evaluation is based on certain physical attributes, namely, physical appearance, aroma, taste etc. The TF-TR (Theaflavin-Thearubigin) based chemical analysis is the most commonly used method by the tea industry for quality assessment. The TF:TR ratio is used as a descriptor of quality of made black tea. However, the subjective evaluation is most commonly used approach by tea industry.

2.2 BLACK TEA PRODUCTION STAGES

The processing of black tea involves a sequence of steps to be followed, namely, plucking, withering, pre-conditioning, cutting–tearing–curling (CTC) followed by fermentation and drying. Quality of leaf is defined at the very first stage i.e. plucking, where, as a conventional practice, the bud and the first two leaves are plucked and the remaining leaves are left back on the plant. After plucking, the process of withering follows, where moisture removal from tea leaves takes place with a draft of warm air passing through leaves spread on troughs having 20 to 100 feet length and 5-8 feet width. The thickness of tea bed is maintained at about 20 cm. during this process (Mahanta & Baruah, 1989). The tea leaves after withering are crushed mechanically in order to segregate the chemical compounds present in them. This process involves cutting, tearing and/or curling process. In CTC machinery, after withering and pre-conditioning phase, leaves are crushed between rollers. Physical attributes of the tea manufactured, such as size of tea granules can be changed by adjusting the pitch of the rollers along with space between them. Leaves obtained at outlet of CTC machine are passed on to the fermentation stage where the leaves are oxidised in presence of air. Dark green colour of the leaves is converted to coppery brown colour and an aroma resembling the smell of an apple begins to emanate. Thereafter, the leaves are sent to the drier where in presence of hot air excess moisture content is shed off. The factors such as hotness of air, flow rate, and quantity of air inside the drying compartment influence the drying process. Lowering of moisture content, formation of black or brown colour, transformation of chlorophyll to pheophytin, formation of some compounds that add to aroma and flavour, etc are a few of those several chemical changes that take place during drying (Bhattacharyya, 2007; Wickremasinghe *et.al.*, 1979).

2.3 FACTORS DETERMINING TEA QUALITY

Quality of made-tea starts getting defined right from the crop level with different ways of plucking and plucking intervals. Normally, the bud and two subsequent leaves are plucked. The remaining leaves are left on the plant. The nature of manure used can also impact the various pigments present in tea leaves. Further, noteworthy distinction in quality is observed with different tea varieties like the constituents of leaves *viz.* phenolic compounds, content of caffeine, etc. in different climatic settings. Caffeine is a key constituent that is responsible for making the tea brisk and creamy. Briskness is related to taste and flavour while creaminess makes the tea liquid turbid when it is allowed to cool and these two elements are essential components that must be present in any good cup of tea. Care has to be taken during the transportation tea leaves and it must be ensured that they are not damaged in transit due to poor handling (Sarma, 1999). From harvesting to packaging, the various stages and processes involved in tea manufacturing affect the quality of finished product. After completion of 70% withering, which means reduction of total weight of leaves from 100% to 70%, the leaves are passed on to next stage of processing where they are cut and finally rolled before being fermented. Fermentation is an enzymatic oxidation procedure during which some chemical changes come about in tea leaves like degradation of proteins; transformation of chlorophyll to pheophytins; formation of certain volatile organic compounds from lipids, amino acids, carotenoids and terpenoids, etc. This process results in the development of two classes of coloured compounds called Theaflavins (TF) and Thearubigins (TR). While TF has golden-yellow colouration, the TR is primarily reddish-brown in colour. TF and TR are the two key chemical attributes that are deciding factors related to appearance and flavour of tea liquid. (Roberts, 1962; Wickremasinghe, 1978; Yamanishi, 1981; Mahanta and Hazarika, 1985; Mahanta, 1988; Borah and Bhuyan, 2003). The making and breaking of chemical compounds in tissues of leaves during fermentation adds to the briskness, strength, body and colour to the final product (Hazarika and Mahanta, 1983; Takeo and Mahanta, 1987). While the briskness as well as strength are directly associated with the amount of TF present, the colour and strength are linked with the concentration of TR. As the fermentation process advances concentration of TF as well as TR begins to increase and the change in the colour of tea can visibly be observed. The optimum ratio between TF and TR is observed corresponding to the peak of the curve (Figure 2.1) which is approximately 1:10. If the fermentation is allowed to proceed beyond this, the concentration of TR keeps on increasing and that of TR keeps on decreasing, with TF gradually degrading into TR. The more concentration of TR achieved upon over fermentation may add rich colour to the tea, but flavour and taste are sacrificed. In order to have perfect combination of taste and appearance one has to adhere to the perfect TF: TR ratio, which is a direct indicator of optimal fermentation. Practically, colour and colour changes should be measured and monitored to assess tea quality during the process of fermentation to correlate the essential information related to the physio-chemical changes that are taking place.

Sorting of black tea into diverse grades on the basis of variations in granule size is being followed in tea industries for quality evaluation. The tea is made to pass through a number of sieves having openings of different sizes, arranged one below another, with the sieve of largest sized opening at the top. These sieves are subjected to constant vibrations using some mechanical arrangement. The diverse tea grades are collected at outlet of the respective sieves. Based on size of the granules, tea is broadly categorized as leaf, brokens, fannings followed by dust, in decreasing order of their granule size (Borah et al., 2007). Some of the commonly used terms to describe black tea are 'attractive' or 'well-made' representing a well made sample of granules with uniform colour and size; 'even' describing a sample containing tea granules of uniform size; 'mixed' representing the presence of different grades together in a sample; 'bold' indicating the presence of pieces of leaves and 'stalky' containing undue presence of stalk.

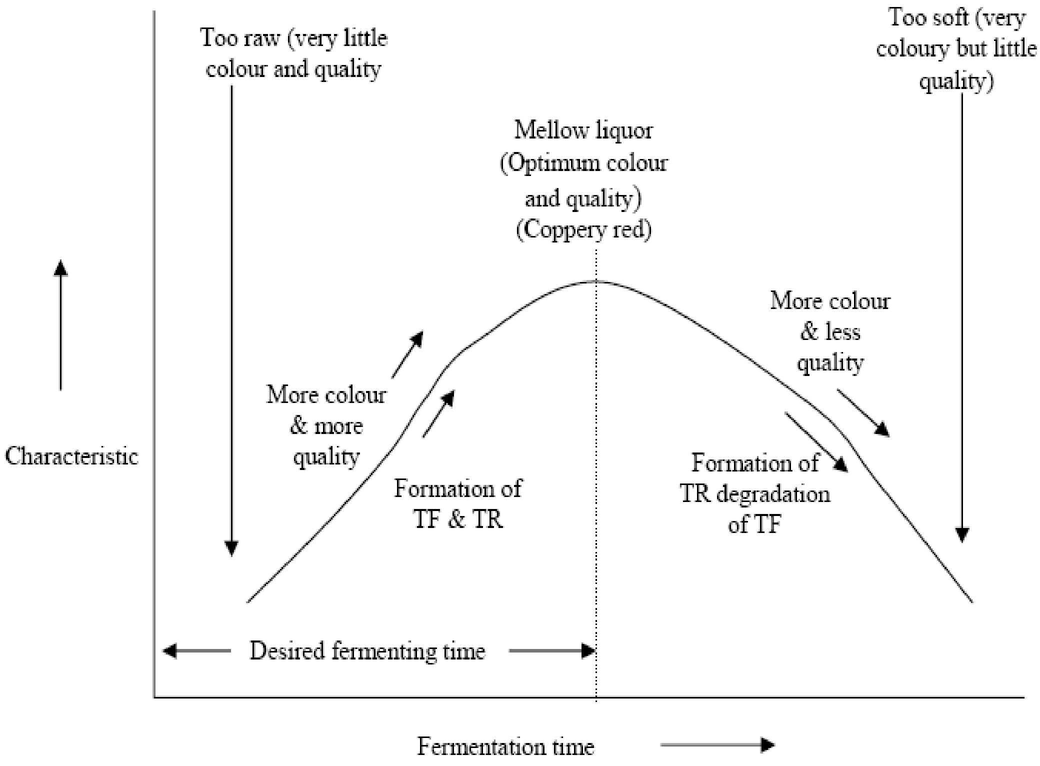


Figure 2.1: Overview of the fermentation process

2.4 TEA QUALITY ASSESSMENT METHODS

In broad perspective tea quality assessment can be categorized into two stages as assessment during fermentation stage and secondly assessment during post fermentation stage or grading stage (Gulati and Ravindranath, 1996; El-Marsy *et.al., 2007*, 1997; Sharma, 2011; Owuor and Obanda, 1998; Taylor *et. al.*,1992, Botheju *et. al.*, 2011, Obanda *et. al*,1997).

2.4.1 Fermentation Stage

During fermentation stage, colour and flavour serve as key parameters used to indicate condition of optimum fermentation. Thus, in order to achieve optimum fermentation, the manufacturing process has to be continuously monitored and controlled till the required colour and flavour is obtained. These colour variations directly correspond to the physical as well as chemical transformations happening all through fermentation while the odour or aroma formed serve as an indicator of nature and quantity of volatile compounds formed during the process. Consequently, these attributes, colour and aroma serve as key parameters for assessment of optimum level of fermentation and hence quality.

The use of use of human sensory panel of trained professionals is a familiar practice followed by tea industry for detection of optimum colour by visual inspection at regular intervals till condition of optimum fermentation is achieved. This technique is presumed to be reliable for subjective estimation of tea quality, if colour is evaluated accurately. However, owing to variations in eye estimation by tea tasters, an inconsistency in matching of tea colour at condition of optimum fermentation is sometimes reported. Machine vision based methods can be of substantial importance in eliminating the deviations due to subjective variability and can serve as alternative approach in estimating the colour changes during fermentation process. Similarly, the flavour is judged by olfaction to decide the completion of the process by tea tasters who give a score to the product on the basis of a number of flavour descriptors. Different tea tasters give their judgement about the same colour and flavour of tea by using diverse levels of quality descriptors. The reason for such variations may be attributed to individual variability, changes in adaptation (attaining less sensitivity due to prolonged exposure), fatigue, or psychological state etc.

2.4.2 Grading Stage

After fermentation, at drier outlet, the tea is segregated into diverse sized granules by passing it through an arrangement of sieves, arranged one over another, with decreasing order of the opening size. Tea granules of different grain sizes collected at the outlet of these sieves are categorized into different grades, namely, Leaf, Brokens, Fannings, Dust, etc. The CTC tea grades are also commonly known as Orange Pekoe, Broken Orange Pekoe, Fanning and Dust. These grades are traded under a large variety of conventional names. The precision and reliability of factory tea grading is maintained by using sieves having quality certification. The granule size for grade allocation may vary between the manufacturers but this approach of using sieve sets spans most of the tea manufacturing sector with minor variations. After separating the different sized tea, they are graded for before packing. Till date, there are no globally accepted standards for defining these tea grades in terms of particle size distribution and the tea grading has been carried out so far by human visual assessment only. Though the quality factor may not come into consideration at the beginning of separation of tea granules into different grades, but right after the separation into different grades, they are tested by tea tasters for assessment of their quality, appearance, taste and aroma, etc. before final packaging.

2.5 MACHINE VISION BASED QUALITY ASSESSMENT

Machine vision based techniques have been employed in recent past for colour recognition in an image of food product and has been reported as an efficient technique for quality examination (Gunasekaran, 1996; Brosnan and Sun, 2002; Gill *et. al*, 2011). Colour is a significant feature on the basis of which an image can be analysed and classified. Since visual colour examination is affected by a variety of parameters such as nature of illumination, condition, direction of observation and individual variability in colour perception, the computer vision based colour analysis can provide an objective and reliable method of colour analysis. In this research, images of tea granules at the drier output stage have been analysed and graded based on their colour, shape, size, texture, moisture and density. The machine vision technique provides a researcher a non destructive non-intrusive alternate approach which is objective unlike the conventional approach of using a human sensory panel which was highly subjective and suffered from human variability.

2.5.1. Machine Vision Set-Up

A machine vision set up by and large has the following elements: lighting mechanism, an imaging device (camera), a frame grabber, a computer and relevant software (Fig. 2.2) (Wang & Sun, 2002). Like human eye, the performance of such system is greatly influenced by intensity as well as nature of lighting. It has been observed that by suitable variation of illumination the appearance of the entity can be considerably changed (Sarkar *et.al.,* 1991). Thus, with the selection of suitable lighting scheme, image quality can be significantly improved and so the performance of the overall system (Novini, 1995).

Gunasekaran (1996) highlighted that a well-made lighting scheme can greatly improve the efficiency of image processing techniques by enhancement of contrast of the image. Reduction in reflection and overall noise can be greatly lowered with the use of better illumination. Some key factors such as nature of source of illumination, the direction and spatial orientation of light source with respect to the object to be illuminated also need to be aptly addressed by the designer (Bachelor, 1985). The illumination techniques can be classified into bright and dark field lighting (Gunasekaran, 2001). While, bright field lighting is used for providing uniform illumination as provided by incandescent lamps, the dark field illumination is lighting from an angle with respect to the surface in order to highlight a feature of interest. It is generally used to highlight surface features.

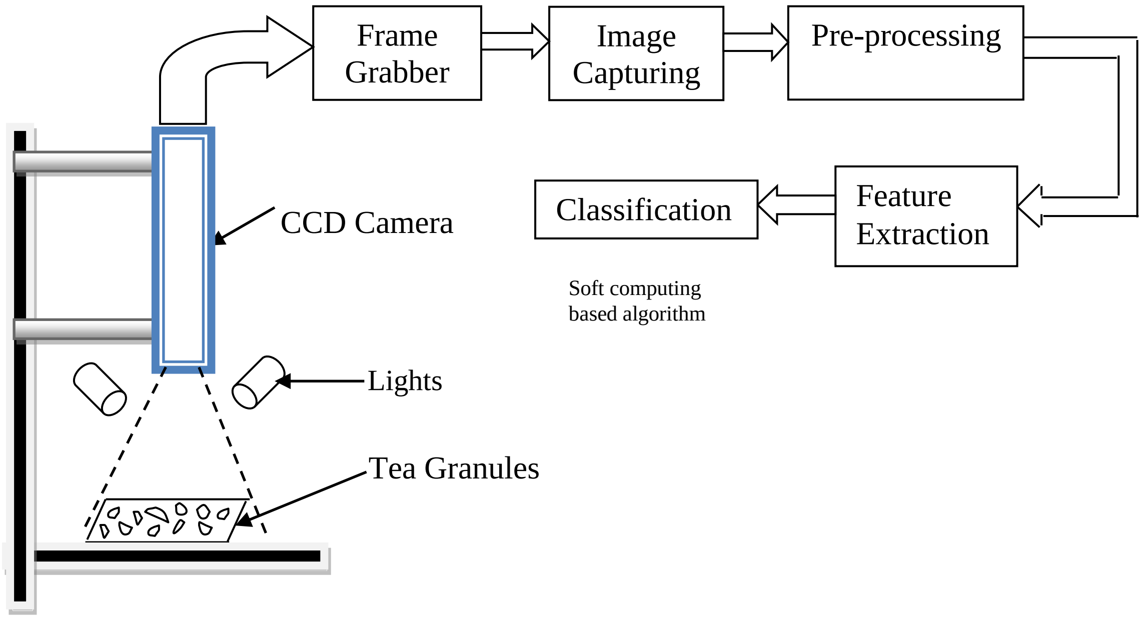


Figure 2.2: Layout of a Computer Vision System

Traditionally, a variety of sensors such as X-ray and ultrasound were employed for image generation. In the modern scenario, charged coupled device (CCD) have become the heart of modern imaging systems. CCD imaging systems can be categorised as area scan or line scan type on the basis of the scanning technique used by them. The area scan type devices comprise of an array of sensors from which image of the object can be obtained on the basis of output which is directly proportional to the incident light. On the contrary, line scan devices use a one line of sensors which repetitively scan at a rate of 2000 times in a minute in order to present a precise image of the entity when it is made to move beneath the sensor (Wallin & Haycock, 1998). Both, monochrome as well as colour imaging devices are extensively finding their use in a wide range of applications (Leemans, *et.al*, 1998; Pearson & Slaughter, 1996; Steinmetz *et. al.*, 1999; Abbasgolipour *et. al.*, 2010). Further, using the frame grabber image data is converted into numeric data for further computational analysis.

Choice of frame grabber is governed by factors like the type of camera output, desired resolution along with processing ability of the digitizer (Gunasekaran & Ding, 1994).

2.6 COLOUR IMAGE PROCESSING

The colour image of tea liquor can serve as a key indicator of its quality and grade. This is done during the process of tea manufacturing to identify the condition of optimum fermentation and at the final stage to assess its grade. This section presents the concept of colour image processing.

The broad areas of colour image processing are full and pseudo (false) image processing. While in the former technique, the image acquisition is done with a full-colour sensor like a CCD camera or colour scanner, in the latter case, a particular colour is allocated to a specific monochrome intensity. Pseudo colour image analysis is all about assignment of colours to gray scale intensities on the basis of a specific criterion. The term “pseudo colour” conveys that colours have been artificially assigned, opposing the true colours. Full colour image processing technique is widely followed now due to the availability of colour sensors and associated hardware for processing colour images. Colour grading is used in the processing of fruits, vegetables and grains (Brosnan and Sun, 2002; Shahin and Symons, 2001). Colour grading usually involves two steps: colour feature representation followed by colour categorization. Colour must be represented in a way that allows it to be aptly categorized.

Getting the image data into an appropriate colour model for the specific application is one of the critical issues encountered in machine vision. There are different colour models available to the researchers which are used in different applications. These colour models enjoy certain merits and demerits over one another. The models that separate intensity from the chromatic properties of light are, in general, considered more useful for analysis of colour of an object in an image. The colour image comprises of three pieces of information per picture element (pixel), i.e. intensities of red, green and blue (RGB) colours. Processing of colour images involves the accurate separation or combination of these three colour spaces.

While dealing with image compression using colour information, the luminance-inphase-quadrature (YIQ) model becomes an obvious choice owing to its redundance of colour information. For instance, when lighting changes are observed across an orange patch, all red, green, and blue parts exhibit a change, but in the YIQ model the I and Q parts stay intact while only the Y part varies (Funt & Finlayson, 1995; Mark, 1998). Thus, an appropriate selection of a colour model for specific application is very important.

A colour model is a mathematical notation used for representing a set of colours. Numerous colour models are available to the researchers in image processing for various applications. The objective of a colour model is to represent the colour in some standard, globally accepted, way. Given below are some of the widely known colour models relevant to the research purpose along with their advantages in colour based system. Commonly used methods in vision analysis include RGB (Red Green Blue), CMY (Cyan Magenta Yellow) and HSI (Hue Saturation Intensity).

2.6.1 RGB Model

The RGB model represents an additive colour scheme wherein red, green, and blue lights are added so as to obtain an arrangement of diverse colours. This model derives its name from the first alphabet of 3 primary colours *viz.* red, green and blue. This model serves a fundamental background for image display in modern display devices. It also finds its application in traditional photography. Upon combining the red, green and blue intensities, the white light is obtained. Modern computers use 24 bits to display the RGB colours. In this model, there are 256 levels of intensities for each of the three constituent colours. Thus, one can possibly have a total of over 16 million colours in 24-bit RGB scheme. The intensities of each of the primary constituent colours can be expressed on a scale of 0-255 where 0 is used to designate least intensity while 255 the highest intensity level.

RGB model uses Cartesian co-ordinate system. The colour space in this model is characterized by a cube with primary colours positioned at corners while black occupies the origin, its diagonally opposite corner is designated white (Fig. 2.3). In other words, the corner farthest away from origin is designated white colour. Gray tone intensities are observed on the diagonal line drawn from the corner of the cube representing the black to the white. On this diagonal each of the primary colours are present in equal proportions. The cube axes defined as R, G and B, can have values in the range of 0-1. The location of red is specified as (1, 0, 0), of blue as (0, 0, 1) and that of green as (0, 1, 0) as white.

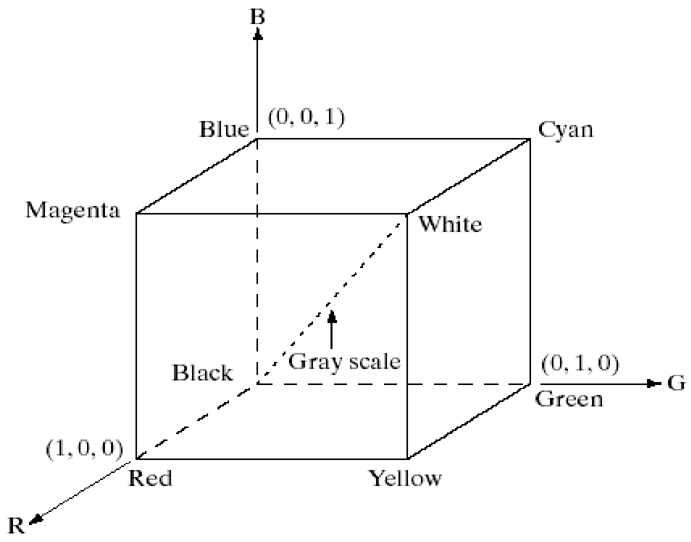


Figure 2.3: RGB colour space

A colour image acquisition is done by using set of filters, responsive to each of the primary constituent colours. When a coloured object is captured using a monochrome device fitted with either of these filters, a monochrome image with intensity relative to response of particular filter is obtained. Doing this repetitively, every time with one of the three different filters results in 3 monochrome images those represent the constituent images corresponding to the primary colours for the same coloured object.

2.6.2 CMY(K) Colour Model

The RGB and CMY (Cyan, Magenta, Yellow) models are very closely related. The primary colours of one form the secondary colours of the other. The CMYK colour model, like CMY, is also a subtractive model, which finds extensive application in coloured printing. The additional alphabet "K" suffixed to CMY here stands for **k**ey or black. This colour scheme is based on the concept of masking the colours, partly or completely against a light background. The ink trims down the light which may be reflect, if not masked. For example, red colour does not reflect from the object if an object surface encrusted with cyan colouring, when illuminated by white colour. This means that red colouration is subtracted from the white colour, which contains equal composition of primary colours, by the cyan. Due to it's this nature this model is referred to as a subtractive model. The RGB to CMY conversion is performed by the following mathematical relation:

$$\begin{bmatrix} C \\ M \\ Y \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} - \begin{bmatrix} R \\ G \\ B \end{bmatrix}$$

Here, it has been believed that all values are kept in the range of 0 to 1. As discussed above, it's evident from the above relation that when light reflects back from the object having cyan layer, the red colouration would be absent. Similar would be case with other two colours as well. The CMYK colour space adds a black component to the CMY model. Although theoretically, when present in equal amounts, cyan, magenta, and yellow must make black but, practically ideal black is not formed. So, in such a situation, addition of black colour solves the problem.

2.6.3 HSI Colour Model

HSI stands for Hue Saturation Intensity and is a well known system used in the field of machine vision. Though RGB and CMY models are interchangeable and suitable for hardware implementations, but they are not suitable for relating colours as the human vision system perceives them. Natural human vision perceives the colour in terms of HSI model. Hue is an attribute that is an indicator of colour purity. The saturation provides an estimate to which extent a colour dilution has been done and intensity describes the colour sensation. The HSI scheme segregates intensity from the rest of two components in a coloured image. This feature makes this colour scheme an obvious choice for development of systems that can very closely match the human perception. Hence, it can be said that, though the RGB colour model is ideal for image colour generation, it is not suitable for use for colour representation. The values of all three components of HSI model can be derived from the RGB model using the mathematical formulae given below:

$$I = \frac{1}{3}(R + G + B)$$

$$H = \cos^{-1}\left\{ \frac{\frac{1}{2}\left[(R-G) + (R-B)\right]}{\sqrt{\left[(R-G)^2 + (R-B)(G-B)\right]}} \right\}$$

$$S = 1 - \frac{3}{(R+G+B)}\left[\min(R, G, B)\right]$$

2.7 IMAGE TEXTURE ANALYSIS

Texture is that visual characteristic of the image that represents spatial information contained in object surfaces and thus categorises a section to a particular class. Texture features include roughness, uniformity, regularity, linearity, phase, frequency, etc. (Tamura *et al.,* 1978). Texture properties permit the human vision system to discriminate among various sections in an image (Bennis & Gagalowicz, 1989). There are many other definitions of textures defined for different applications but no universally acceptable texture discrimination model is yet available. The methods of extracting textural features are broadly characterized as statistical methods, geometrical methods, model-based methods and the transform-based methods.

2.7.1 Statistical Textural Methods

Statistical methods are based on analysis of spatial arrangement of gray levels. Features are computed locally at every point in an image and statistics are derived from distribution of these features. Depending upon the number of picture elements (pixels) used to define a feature, these methods are further termed as first order, second order or higher order. The first order features are based on one pixel while the second and third order is based on two and three picture elements, respectively. First order features evaluate the attributes related to a single picture element, irrespective of its special location and orientation with respect to other ones. The higher order features evaluate the characteristics of two or more picture elements that are spatially located at a specific orientation with respect to each other.

A well known technique used for analysing textural attributes involves estimation of features from gray level co-occurrence matrix, popularly known as GLCM. This method was presented by Haralick in the early 1970s for analysis of remotely sensed images (Haralick *et al.,* 1973). A GLCM presents the second-order joint probability related to occurring of two gray levels i and j for two picture elements for which the spatial connection is defined in terms of distance d and angle θ. For a coarse texture and a low value of distance compared to size of textural element, the pairs of points that are apart by distance d must have same gray values. On the contrary, if texture is fine and d is equivalent to size of texture, the gray of points distance d apart are expected to be reasonably dissimilar, and in such an event GLCM values are rather uniform. A number of improvements have been proposed after this pioneering work by Haralick. The concept of Local Binary Pattern operator by Ojala (1996) incorporated the occurrence statistics of localised microstructures thereby integrating statistical as well as structural techniques to textural analysis. He further gave the concept of signed differences which is considered to be a landmark development in the field of texture analysis (Ojala. *Et. al,* 2001). The other prominent developments in this are the computation of autocorrelation function by Kaizer (1955), that is being used for analysing the textural uniformity and the gray level run lengths by Galloway (1975) Though these methods were popular in their times, later with the constant improvements coming up in this area the performance of these methods leave much to be desired, so eventually they became obsolete (Conners & Harlow, 1980). In the recent past, Miyamoto and Merryman (2009) made an attempt to optimize the computation of the Haralick texture features with an objective to reduce the computational runtime. The speed of constructing the co-occurrence matrices for their model was attributed to the recursive blocking algorithm, while the actual feature calculations were optimized using concatenation of redundancies as well as unrolling. They claimed an overall increased performance of the system by approximately a factor of 2.

2.7.2 Geometrical Textural Methods

Geometrical methods characterize the texture in image as being made of texture elements. The textural element is also called a texel. These methods are based on the geometric characteristics of the texels and the rules governing their spatial organization. Voronoi tessellation features are quite popular under this category of texture analysis (Tuceryan and Jain, 1990). In this method, a tessellation is developed from the texture tokens. Tokens can either be simply the points having large gradients in an image or they can be complicated features like closed borders. Algorithm proposed in this study extracted textural tokens from gray scale images in which a Laplacian-of-Gaussian (LoG) filter is used for selecting the pixels which are located on local intensity maxima in image obtained after filtering. Further, the analysis of connected components is carried out on the two tone image with eight nearest neighbours such that every connected component defined a texel (or token). Now, Voronoi tessellation is constructed from all the tokens extracted. Further, the features are extracted from each cell of Voronoi tessellation followed by grouping of tokens with like features in order to develop the regions having identical textural profile.

The textural features related to Voronoi polygons are extensively utilized for segmentation problems in the images containing complex textures. Edge based algorithm for segmentation is used which statistically compares the nearest collection of texels. A huge difference amongst the textural features in this case indicates the presence of an edge. It has been claimed that the developed algorithm can successfully segment the gray scale and synthetic textures with equal accuracy (Tuceryan & Jain, 1998). However, the practical viability of these methods is very restricted as they can comfortably address the problems related to regular textures only. (Bharati *et al.,* 2004).

2.7.3 Model Based Textural Methods

Model-based approaches create an empirical model of every pixel in an image on the basis of weighted mean of neighbouring pixel intensities. These computed attributes are then utilized as textural features. The well known model based methods for textural analysis are autoregressive (AR) models (Sarkar *et al.,* 1997), Markov random fields (Cross & Jain, 1983) and fractal models (Bharati *et al.,* 2004).

Markov random fields (MRFs) is a well known and established technique often utilized for texture synthesis (Cross & Jain, 1983) cataloguing (Chellappa & Chatterjee, 1985; Khotanzadand & Kashyap, 1987) that operates by capturing the local contextual order in the image. These models are based on the assumption that the pixel intensity is a function of intensities of its adjacent pixels. The neighbour of a particular location *l* can be defined in many ways. The four-connected neighbours of *l* are termed as its first order neighbours while its eight-connected neighbours form its second order neighbours. The discrete Gibbs random field (GRF) is used for assignment of probability mass function to the whole of image, which is represented as *NxN* array. It is a well established fact that a unique Gibbs random field exists for each Markov random field (Besag, 1974). According to this concept texture can be modelled globally by establishing total energy of *NxN* array or it can be modelled locally by specification of local connections of neighbouring picture elements. Generally a group of attributes can completely define and model the textural characteristics of the image. In the field of texture synthesis, these values id controlled can lead to generation of the desired type of texture. An attempt was made to synthesize the textures using this approach (Cross and Jain, 1983). The attributes were computed for natural texture and using these attributes attempt was made to produce synthetic texture. It was observed that the response of the system was quiet satisfactory as far as micro textures were concerned. However, it miserably failed with the non homogeneous textures. (Tuceryan & Jain, 1998).

2.7.4 Signal Processing based Textural Methods

Signal processing based approaches like Fourier (Rosenfeld & Weszka, 1980), Gabor (Daugman, 1985; Bovik *et al.,* 1990) and wavelet transformations (Mallat, 1989; Laine & Fan, 1993; Lu *et al.,* 1997) characterize an image in a space where the co-ordinate system presents an interpretation that is directly connected with the descriptors of texture. Spatial domain filters present a direct approach to capture textural features in an image. This method tries to find the texture edge density per unit area. The edges in such cases are usually calculated using Laplacian operator (Voorhees & Poggio, 1987). Another popular technique is the frequency analysis in Fourier domain (Montes, 1988) which describes only the global recurrence of gray values in the image surface by identification of peaks having higher energy in spectrum. Also, it is unable to draw any useful information about the surface characteristics of the image. Overall, the methods based on Fourier transformation generally are not able to yield satisfactory results in such problems. Though the Short-term Fourier Transform (STFT) is viewed as one way to obtain both spatial information and frequency localization this technique too, has its limited capabilities which are restricted by a fixed window size. Also, this procedure is computationally complex for natural texture applications.

In the recent past, Gabor filters have also been in focus as they provide better spatial localization than all previously described techniques. However the key shortcoming of Gabor transform is the absence of unique filter resolution at which spatial structure can be localized while handling natural textures. On the contrary, wavelet transform can be viewed as a suitable alternative for analyzing a signal at diverse scales (Unser, 1995). Further, wavelet transform can suitably represent textures at a suitable scale by precise variation of spatial resolution. Also, a wide variety of choices are available while choosing the wavelet function for a particular application. In spite of its non translation-invariant character (Brady & Xie, 1996: Sharma *et al.,* 1980), wavelet transform is considered as a preferred choice for textural segmentation.

Arivazhagan (2003) proposed a Discrete Wavelet Transformation (DWT) based approach for texture classification. In this method, image is disintegrated into four sub-bands by application of DWT (Fig. 2.4(a)). The sub-bands obtained are designated as LH1, HL1, HH1 and LL1. While the first three represent the details, which are the fine scale components, the latter one represents approximations which are the coarse level coefficients. For further evaluation of next level of coefficients, the LL1 is subjected to decomposition (Fig. 2.4 (b)). Similarly, further decomposition can be carried out with LL2 and this procedure may continue till the desired scale is achieved. The coefficients estimated from the decomposed images serve as crucial attributes that can further be used for texture cataloguing. The values of textural attributes computed from the sub-band images distinctively portray a texture.

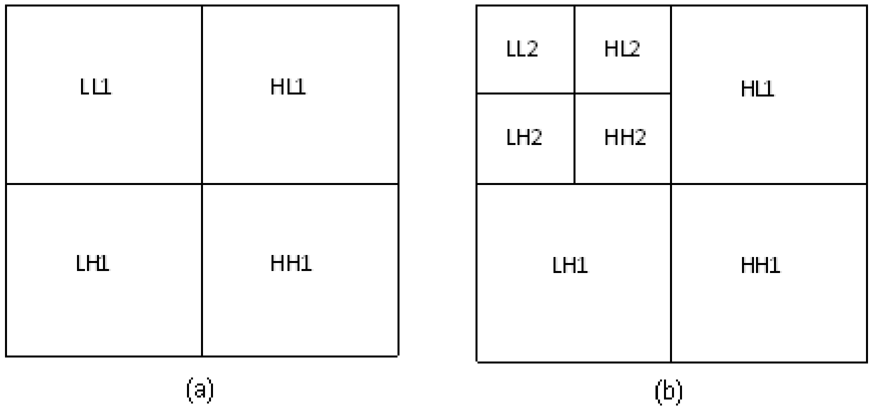


Figure 2.4: Image decomposition (a) Level - 1 (b) Level - 2

The classification problem is sub-divided into two steps, with training followed by categorization. During training, images with known textures are disintegrating by DWT. The features are computed from the sub-band images and stored in database. Finally for categorization of unidentified texture, image is disintegrated by DWT and features are computed. Eventually, by comparing the features obtained with those present in the database the unidentified texture is categorized.

2.8 ANALYSIS OF MORPHOLOGICAL FEATURES

Morphology of an entity is the related to analysis of its geometrical attributes. By morphologically analyzing the image an object can be segregated from the background followed by filtering, segmentation and, finally, computing the features of interest that uniquely represent that object. The fundamental morphological procedure involves dilation along with erosion. While, dilation appends additional pixels to border lines of objects in the image, the erosion is all about eliminating them from the borders. In Paliwal's (2004) work related cataloguing of cereal grains, it was observed that geometric descriptors gave better performance than other features. This is in direct agreement with a few of the earlier studies that have also given their verdict in favour of geometrical attributes over the other ones while dealing with the problems of similar nature (Paliwal *et.al.*, 2004)

Researchers have effectively handled the issues related to identification of objects in an image according to their physical parameters such as shape, size, area, perimeter, etc., (Garbay *et.al.*,, 1986). For non-singulated images (ones in which the objects touch each other) the problem of image segmentation and separation is a tedious job. However, these parameters can be estimated in a relatively convenient manner in case of singulated images (ones in which the objects don't touch each other). A common practice for non-singulated images is to consider global parameters such as total area occupied by the objects and then compute the average area so as to give an approximate estimate of the object size (Bisconte & Margules, 1980). However, they are unable to deliver morphological information pertaining to a particular entity. In this thesis, an approach derived from morphologically segmented images has been followed. Further, the features are computed and shape is analyzed. For the purpose of implementation, this method is split into four sections (Fig.2.5).

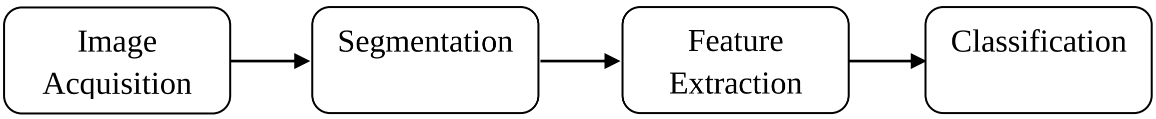


Figure 2.5: Generalized layout of the model

Segmentation is the first procedure that is applied on acquired image for segregation of regions of interest in addition to removal of noise and unwanted sections. Further, useful information in the form of features is extracted from the segmented images. Finally, classification of extracted features can be done by using soft computing based methods like ANN, FL, etc. ANN classifier has been used for the present research problem.

2.9 DENSITY MEASUREMENT

The knowledge of the bulk density of made tea is essential for comparison of different samples of tea on the basis of weight of a given volume of leaves. It is an important factor in filling packets correctly for the retail sale and for controlling the mass of instant tea delivered to the vending machines. Bulk density of made tea varies according to its history of handling, compaction and powder breakdown effects. Density can be explained in two ways - Bulk (un-compacted density) and Tapped (compacted density).

2.9.1 Un-compacted Density

Un-compacted density is defined as the ratio between the mass of a substance in un-compacted form and the volume of same substance along with the share occupied by voids. Thus it has been observed that the overall density is dependent on the density of substance of interest along with the way they are spatially arranged. The commonly used units for expressing density are grams/cm^3. The bulk characteristics of granular or powdery substances depend on methods of sample preparation as well as handling. Density of a substance assumes critical importance in the issues related to packing and even a minor disturbance can lead to substantial changes in density. Density is a complicated variable for precise measurement and while documenting the results, the procedure for carrying out the measurement must be indicated.

Bulk density measurement is carried out by estimating the mass of sample held by a container of known volume.

2.9.1.1 Measurement using a graduated cylinder

A sufficient amount of sample to carry out the measurement is passed through an opening having aperture of nearly 1.0 mm into a graduated cylinder. The agglomerates formed during storage must be broken and it should be done gently in order to avoid any change to the nature of substance. Further the sample is poured into a cylindrical container having volume 250 ml. Then the sample holder is carefully levelled without compacting and the sample weight is measured. From the sample weight and the volume of container, the value of density for the particular sample is evaluated and recorded. It is always recommended to conduct repetitive measurements for estimation of density.

If sample density is extremely less or very high, then the constraint of having minimum amount of sample can be relaxed. However, in such cases the mass of sample used must be specified while reporting the final results (WHO, 2012).

2.9.1.2 Measurement using a volumeter

The apparatus used for method (Fig. 2.6) has an arrangement with a funnel at the top for accepting the sample with an opening of 1.0 mm diameter. The funnel located above the baffle box that is used for regularizing the sample flow as it passes through it. Under the baffle box a collecting cone is located that is used for sample collection. Finally, the sample is poured into the sample holder.

The sample is poured into the sample holder till the top brim. As a convention, a minimal amount of 25 cubic centimetres of sample must be taken while using a cylindrical sample holder and 35 cubic centimetres for cubic sample holder. The top of the sample holder should be levelled with utmost care using a spatula. The weight of the material along with that of the sample holder is measured at this stage. Researchers should ensure that the weight of empty sample holder is reduced from this measurement. Density is then evaluated by dividing the mass by volume. It is recommended to take more than two measurements by drawing the samples from the same content domain (WHO, 2012).

2.9.2 Compacted Density

Compacted density is the enhanced density that is obtained when mechanical vibrations are used to shake the sample holder with the sample inside it. After filling the sample holder with the sample up to the top brim, the weight of the sample is measured. Now, the sample holder is mechanically vibrated so that the sample particles adjust themselves and occupy the void spaces inside the sample holder. These rearrangements of sample particles allow them to have a more dense packing and as consequently the level of sample within the sample holder drops down significantly. Now according to the reduced level the new volume occupied by the known mass of sample is computed and from the values of mass and volume the compacted density is estimated and recorded. Measurement of compacted bulk density uses tapping mechanism using cam, which lifts shaft and rotates at 250 revolutions per minute (Fig. 2.7) (WHO, 2012).

2.10 MEASUREMENT OF MOISTURE CONTENT

The amount of moisture present in tea leaves at the drier stage serve as critical determinants of its overall quality and shelf life. It has been observed that the presence of more moisture than the prescribed limits can make the tea more susceptible to fungal attack. Till date, no dedicated and standardised scheme for precise evaluation of moisture in the dried tea granules has been adopted at the post production phase (Bhuyan *et. al.*, 1996). Though, there is no thumb rule followed in this regard the tea producers try to keep the moisture content of their ready product well below 5 percent.

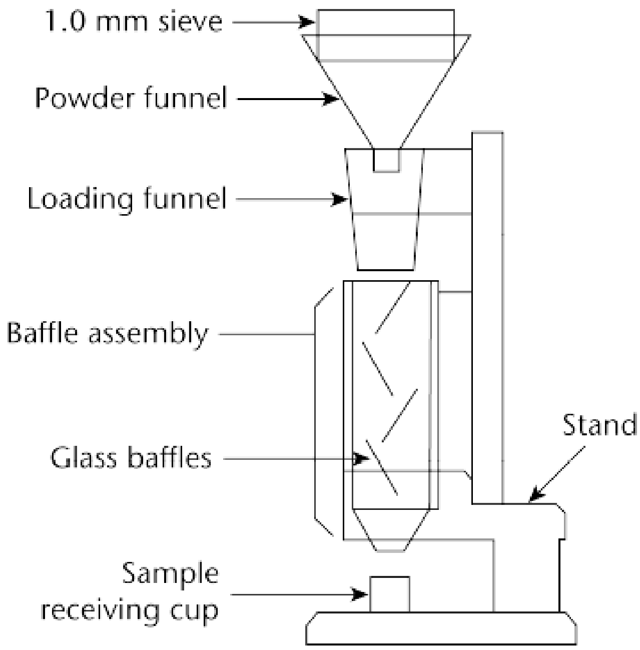


Figure 2.6: Volumeter

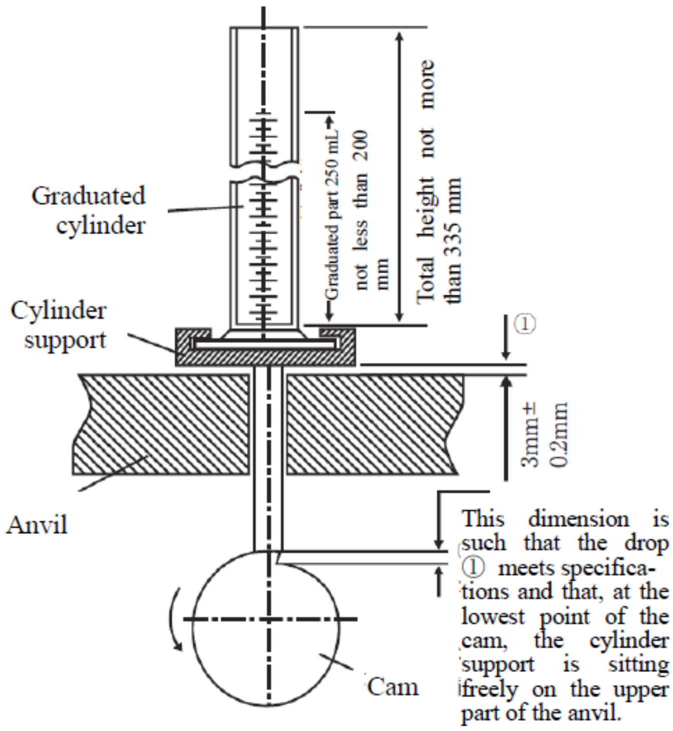


Figure 2.7: System for estimating Tapped Density

Commonly moisture estimation is done by gravimetric or IR in addition to the evaluation by a human taster. The limitation of weight method is that it involves measuring the weight of samples having equal volumes.

Since tea is composed of fine granules of diverse sizes, weight of samples taken is likely to have a large dependence on the sample density. Since the samples of diverse grades have different sized granules, they are expected to return different weights, thus leading to wrongful interpretation. Also, the evaluation of human expert being subjective in nature is not reliable as it can be affected by personal bias and preferences. Such approaches exhibit a large time gap between rate of manufacture and rate of estimation. Moreover, being essentially the laboratory approaches they are highly unsuitable for online screening.

The electrical characteristics of a material *viz.* resistive, capacitive, and inductive can be utilized for estimation of moisture content of various materials. Resistive probes have been in use for measuring the moisture content in wooden walls (Tsongas & Nelson, 1991). Relation between wooden resistance and moisture content has also been reported (Caril and Tenwolde, 1996). Capacitive sensors also have been successfully used for estimation of moisture content of various substances. A large number of systems have been designed for assessment of moisture content of materials like as ceramics, food products, paper, etc. (Abegaonkar *et. al.*, 1999; Nalson *et. al.*, 1992; Lasri *et. al.*, 1991, Sundara-Rajan *et. al.*, 2004). However, no benchmark work is reported for detection of moisture in tea granules especially at post production stage. (Hazarika *et. al.*, 2006).

Thermo-gravimetric analysis (TGA) in recent times has gained wide popularity for its high degree of accuracy and reliability. In this method weight variation in the substance is measured in response to changes in temperature at some preset rate in the controlled environment. The main applications of this approach are evaluation of decomposition temperature, estimation of moisture content of organic and inorganic materials and the ratio of constituent elements in any compound.

In the TGA sample is placed in an environment whose temperature is gradually increased at some predestined rate and during this procedure the weight of the sample is constantly monitored as well as recorded by an in-built precision balance. In TGA process, large decrease is witnessed when a volatile compound decays. Similar decrease in mass is observed when chemical phenomenon like combustion takes place. On the contrary, the physical changes like the phase transformation do not exhibit any mass changes. For the purpose of analysis, the variations in sample mass are plotted with respect to temperature in order to highlight the key phenomenon taking place within the sample.

2.11 DATA CLASSIFICATION

In order to solve a particular problem, many soft computing methods are available to the researchers. These methods learn from the input stimuli and adapt accordingly and can solve the problems by applying the knowledge gained from past experience. Commonly used approaches for data cataloguing are GA, FL and ANN. The fundamental principles of ANNs have been discussed in the following section. ANNs are computational structures which mimic the ideology and behaviour of human brain. The knowledge base presented to the network has direct impact on the structural changes taking place within the network as it modifies or trains itself in response to the inputs as well as goals offered to it. These networks are essentially non-linear tools for data analysis which model the multifarious connections that exist between input-output pairs. In early 40's the concept of artificial neuron was given by McCulloch (McCulloch, et. al., 1943; Widrow & Lehr, 1990). The ANN model consists of three key elements, namely, the processing elements in which the weighted inputs are summed (artificial neuron), an activation function (φ) which translates the activation value; and the output (o_j) of the model (Fig. 2.8).

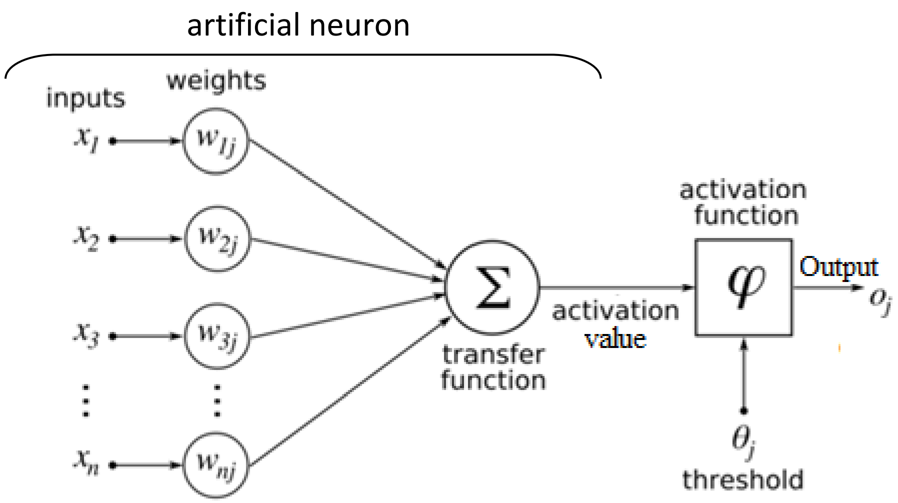


Figure 2.8: Artificial Neural Network

2.11.1 Multi Layer Perceptron

MLP is an extensively used network arrangement that is reportedly applied in a number of practical problems. This network comprises of an input layer, one or more hidden layers, and an output layer. The input neurons are identical in count as the number of inputs given to the ANN. The neurons in diverse layers are interrelated in a manner that the output generated by any layer proliferates to the succeeding layer. The architecture of the MLP and the interrelationships amongst different layers has been illustrated in Fig. 2.9.

In the perceptron network, neurons compute weighted sum of inputs followed by transforming it by use of an activation function. The network goes through supervised training phase during which it is presented with training inputs along with targets outputs. The network acquires knowledge from the inputs by updating the connection strengths between the various neurons. One of the most common algorithms for this purpose is the Rumelhart's error back-propagation (1986).

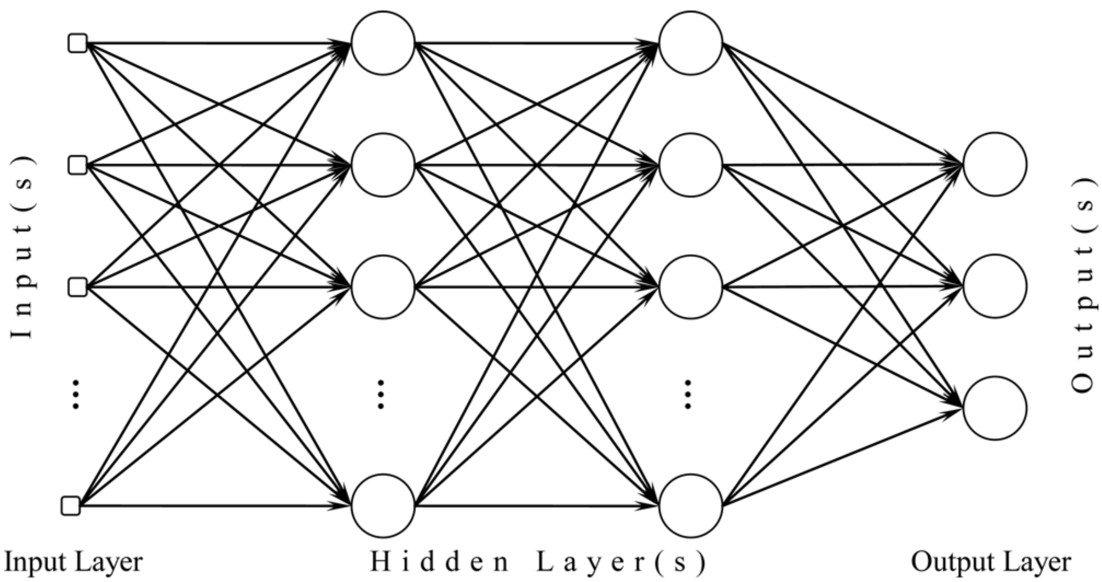


Figure 2.9: Architecture of MLP

In the back propagation training the outputs are computed in response to the inputs presented to the network. Further the errors are computed from the values of desired and target outputs. The weights of the network are updated by sweeping back the error produced. This is repeated for various input-output pairs. Initially weight values are kept small and are chosen randomly.

2.11.2 Probabilistic Neural Network

The concept of PNN is derived from the Bayesian sorting. It is a feed-forward network created by Specht in 1990. Since it is easy to train and is based on a strong statistical framework, PNN is viewed a popular approach addressing issues related to cataloguing and pattern recognition. Further, an improvement over the PNN was presented by Berthold & Diamond (1998) in the form of constructively trained PNN in which new hidden neurons are introduced whenever required and adjustment of the shape of already existing units is done individually in order to minimize misclassification. Before the addition of neurons, an assessment is done whether the existing network can execute the expected task or not. If it is capable of doing it, then by making the necessary adjustments the next training input is presented, or else a neuron is introduced in the hidden layer. This result in relatively compact networks compared to Specht's PNNs and, thus, allows the usage of larger data sets and making the PNN computationally lightweight. Moreover, these networks are small due to absence of redundant neurons in the hidden layer.

CHAPTER 3

METHODOLOGY

Grading of black tea into diverse grades can be done on account of its physical attributes such as morphology, colour, texture, moisture and density. It has been a significant post production process that determines the overall quality of the tea produced. Conventionally, the tea industry relies on the human sensory panel for the grading process. The human evaluation, though has been in process for a long time, is subjective in nature and suffers from variability in evaluation when done by different tea tasters. Efficient grading of tea requires a high degree of sensing ability and intelligence for discriminating the produce into different grades. On the basis of visual inspection, the tea tasters classify tea as leaf, brokens, fannings and dust.

With the growing concern regarding quality of agro and food products, researchers in the area of tea production have been exploring modern techniques for grading of tea produce. Due to inherent shortcomings of conventional human judgement based methods like subjective nature of evaluation and inter observer variability, the grading process cannot be standardized in its present form. The machine vision based system for grading of black tea that has been presented in the current work is a non-destructive approach for grade evaluation. Also, the assessment done using the vision system is objective in nature and is free from any human variability or bias.

In the light of these issues, the work has been carried out for effective determination of shape and size of the tea granules after the drying process using computer vision based method. The scope of present work has been restricted to quality determination of black tea only. In the following sections, the procedures adopted for estimation of various physical parameters have been presented.

3.1. ESTIMATION OF MORPHOLOGICAL PARAMETERS

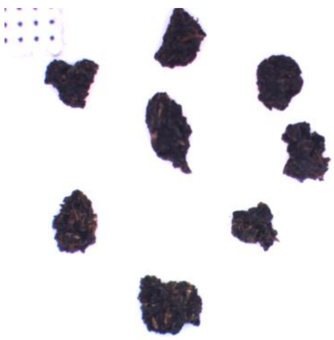
Black tea has been graded on the basis of its granule size as leaf, brokens, fannings and dust. Presently, the grading has been done by separating the different sized tea granules from each other by passing them through sieves of different sizes. This has been purely a non standardized mechanical approach and the sieve size may differ from one unit to another.

This can be efficiently done using a computer vision system by estimation of certain morphological or geometric features of tea granules such as area, perimeter, aspect ratio, etc.

3.1.1. Image Acquisition and Experimental Set-up

The black tea samples of four standard grades i.e. leaf, brokens, fannings and dust, were procured and were utilised for the experiments. The four standard graded samples having different grain size and shapes were assigned the classes L, B, F and D on the basis of their quality and cost index. The procured standard samples of four diverse grades of tea were collected from tea manufacturing industries during the sorting process and were duly graded by human experts according to their quality index.

The imaging system used for estimation of morphological features related to shape and size such as area, perimeter and aspect ratio was a flatbed Scanner, Canon Lide 110 at a resolution of 600 dpi (dots per inch). The tea granules were spread on the bed of scanner in such a way that the granules do not touch each other. Such image setup would be referred to as singulated image in the coming pages, where every single object did not touch the other one (Fig. 3.1(a)). In such a setup, the size of each and every grain can be determined by calculation of the contour of the grain by considering each particular grain as a separate entity.



(a) Singulated Image

(b) Non-Singulated Image

Figure 3.1

In case the grains are touching each other, i.e. the case of non-singulated images, then some overlapping of the grains is observed (Fig. 3.1(b)). Such overlapping increases the chances of wrongful estimation of morphological parameters. This is so because by computer vision, measurement is done by calculation of the effective contour and in case of objects touching each other, the estimated contour would be different from the actual one. In addition to this, it can never be predicted accurately as to how many grains are touching together in a particular situation. All these issues make the problem complicated for estimation of morphological parameters in case of non-singulated images. Due to these reasons, spreading the tea granules in singulated fashion was the preferred method of imaging for estimation of shape and size.

3.1.2 Image database

The images were acquired for all four grades of tea samples namely leaf, brokens, fannings and dust (Fig. 3.2). For each grade, 8 images were taken with the tea granules drawn randomly from the same population. These standard samples of four diverse classes of tea were collected from tea manufacturers during the sorting process and were duly graded by human experts.

Leaf Brokens Fannings Dust

Figure 3.2: Acquired images for different tea grades

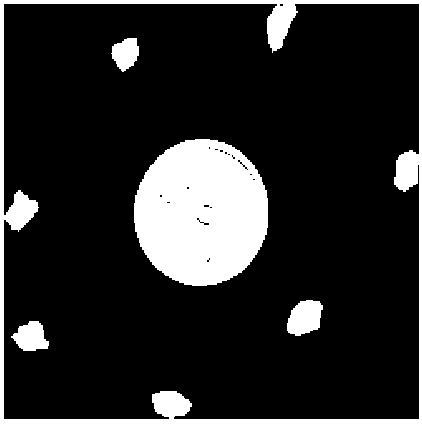
3.1.3 Segmentation

Before proceeding to feature extraction stage, the segmentation involves separation of dark coloured tea granules from the light background with the purpose of segregating the granules from the remaining image. When image was observed, the tea granules can be clearly seen as large dark spots against the white background. Many segmentation schemes are suggested by researchers *viz.* edge detection, thresholding, histogram thresholding, etc. (Gonzalez, & Wintz, 1987; Sonka *et.al.*, 1993; Pratt, 1981; Liedtke *rt.al.*, 1987) but none of them takes into account a specific characteristic of tea granules i.e. its shape. In the present work, an approach based on mathematical morphology has been chosen. If used in an appropriate manner the mathematical morphological operations can extract the fundamental geometric features (Haralick *et. al*, 1987).

The four elementary morphological operations are erosion, dilation, opening and closing. In practice, erosion and dilation operations are always employed in pairs, though the sequence can be different for different applications. If dilation-erosion sequence has been implemented, its termed as closing and if erosion-dilation has been adopted, its termed as opening. However, irrespective of sequence, iteratively applied erosions and dilations result in riddance of definite sections that are small in size compared to the structuring-element. For instance, the image opened with a disc shaped element smoothens the curves, eliminates small islands as well as sharp peaks. On the contrary, while closing the image with disc as structuring element, contours are smoothened, small holes are eliminated and narrow gaps are filled on the contour. Its worth mentioning here that the image transformations comprising of iteratively employed dilations and erosions are idempotent in nature which means that their reapplication does not further affect the previously transformed results. Morphological image filtering by opening or closing operations was analogous to an ideal non-realizable band pass filter of conventional linear filtering.

In the present work, since tea leaves were captured against a white background as a convention, a two tone colour approach comprising of black for dark objects and white for lighter ones was adopted. As a first step image was opened with a disc having dimensions comparable to that of tea granules. This resulted in eradication of those sections from the images that are small in size compared to the structuring-element and the corresponding space was occupied by white coloration. While choosing the size of disc it must be ensured that it should be large enough to eliminate all the objects which are not of prime interest. In this case, the disc shaped structuring element was preferred due to resemblance of tea granules with the disc shape. For instance, if any other structural element other than the disc were used, i.e. a square or rectangular, then a reconstruction operation must be included after opening with square element as the reconstruction operation allows recovering the precise shapes of all the remaining items in an image whilst maintaining the consequence of procedures implemented at the preceding stage. The next step was the thresholding of the image obtained above, which clearly isolated the granules from the background and any noise, if present. The original image and the image obtained after the sequence of morphological operations and thresholding are shown in Fig 3.3. In the present work, the description was wholly on the basis of on opening due to its famous filtering capabilities.

(a) Original Image



(b) Image after opening and Thresholding

Figure 3.3

3.1.4 Feature Extraction

Area and perimeter: Area and Perimeter were considered to be significant parameters in order to discriminate amongst various grades of tea based on its granule size. Since different tea grades differ in granule size, the estimation of area and perimeter can play a key role in discriminating between the grades. The measurement was carried out for 8 images each of four different grades and average area and average perimeter for all the granules of all ten representative images were computed. The computation of area was done for images of various standard grades of tea in MATLAB environment with the use of image processing toolbox using 'regionprops' function. This function defines area as a scalar quantity and returns its value in terms of actual number of pixels present in an area of interest. In order to convert the value in pixels into standard units of area i.e. m^2, cm^2, or mm^2, a calibration was required to be done in order to establish a relation between standard units of area and pixel measurement returned by MATLAB. So, for the purpose of calibration, a coin of rupees two denomination was used for having physical diameter of 24.8mm. Similarly, the perimeter which is defined as the length of border is measured for various grades of tea.

Aspect ratio: Aspect ratio is the relation between the major and minor axes length. It is also significant attribute that gives important information regarding shape of the object under consideration. In MATLAB major/minor axis length is defined as length (in pixels) of the major/minor axis of an ellipse having identical normalized second central moments as the region. Major and minor axes lengths are estimated using ‘regionprops’ function and from the obtained values, the aspect ratios for various grades of tea are computed. The aspect ratios for the three grades of black tea, i.e. brokens, fannings and dust were observed (Table 1) to be overlapping and, thus, aspect ratio cannot be used as a significant metric for discriminating between various grades of tea.

3.1.5 Feature Classification

It has been observed that various grades of black tea can be distinguished on account of geometrical attributes and can be categorized into different grades by using ANN technique. In order to discriminate the grades on account of these attributes, MLP model has been adopted. The features extracted in the previous section are used for classification of images on the basis of shape and size of the tea granules present in them.

As already discussed in chapter 2, the ANN behave analogous to the biological neural networks. They comprise of input neurons, axons, dendrites, neuronal hidden and output layers and transfer functions. In case of human brain, when an image is presented to a human being, the information is read through eyes and is stored in the brain for processing. For the recognition of an object, the human brain processes the data related to appearance, shape, size and colour of the object before arriving at a decision regarding the nature and class of object. It is done by comparing the object with one previously observed object that has been memorized by the brain. In other words, human brain makes the decision related to present problem on the basis of its previously acquired knowledge and this concept of making the network learn and then taking the decision is applied using ANN based method. Thus, the ANN implementation is a two phase process comprising of training of network followed by the testing. During training, network learns about a definite shape when different patterns are presented to it. The learned knowledge is stored as inter-unit connection strengths or weights and is constantly updated each time when a new pattern or object is presented to the ANN by a process of weights adaptation.

***MLP structure and implementation*:** MLP has been employed as a classification tool for discrimination between the diverse grades of tea on the basis of shape and size using area, perimeter and aspect ratio as key parameters. The image database used for network training comprised of images of four diverse grades viz., leaf, brokens, fannings and dust. The three layered MLP network was developed having 3 input, 28 hidden and an output neuron. The training function used was the LM backpropagation (*trainlm*) which update its connection weights values according to LM optimization. The *trainlm* function is one of the quickest backpropagation algorithms. This algorithm has been highly preferred for problems associated with supervised learning although its large memory requirements make it unsuitable for certain set of problems. GDM (*learngdm*) is used as learning while MSE as performance function. MSE estimates the performance of MLP in accordance with mean-square-errors. The network is trained using these functions. The hyperbolic tangent sigmoidal transfer function is employed for hidden while linear function is employed for output layer neurons. The network returned 100% correct classifications.

3.1.6 Statistical Validation of Feature Data

ANOVA is a statistical technique developed to analyze the experimental data. Initially, it was used for the analysis of agricultural experiments to study the impact of various factors such as use of diverse types of seeds, fertilizers and agricultural practices on the yield but soon its applications have extended to many fields of research. With this method, researcher can breakdown the total variance of a variable into additive components which may be attributed to various different factors. These factors may be visualized as causes or sources of variation of the variable to be analyzed. This method when applied to experimental data, assumes a certain design of experiment, which determines the number of relevant factors or causes of variation and the logical significance of each one of them. From the definition of analysis of variance, its clear that this method is conceptually the same as regression analysis. However, the main difference is that the regression analysis provides numerical values for the influence of the various explanatory factors on the dependent variable, in addition to the information concerning the breaking down of the total variance ratio into the additive components while the analysis of variance provides only the latter type of information. Both the ANOVA and regression analysis have as their objective the determination of the various factors which cause variations of the dependent variable (Koutsoyiannis, 2001).

In the present work, for statistical validation of results, one-way ANOVA was applied to the database comprising of computed morphological features. ANOVA is an established way to test the equality of three or more means at one time by using variances. The feature data from image analysis were examined for four different grades of tea to establish whether different grades of processed black tea were statistically different from each other. The mean values of each feature for four different tea grades were compared by applying ANOVA with a significance level of 0.05. Variance ratio (F*) is computed for each feature set as:

$$F^{*} = \frac{\text{estimated variance from 'between'-the - means variation}}{\text{estimated variance from 'within'- the - means variation}}$$

The estimated (or observed) value of variance is compared with theoretical value of $F_{0.05}$ at known level of significance (5% in this case). The theoretical (or critical) value of F is that value of F which defines critical region of test at particular level of significance (Koutsoyiannis, 2001). In case $F^{*} > F_{0.05}$, the difference between means is significant and the populations, from which the samples are drawn, do differ substantially from one another. High value of F indicates that means for the groups vary, as a minimum, moderately from one another. On the other hand, high F depicts that most of the means are comparable but for one. In general, greater the discrepancy between two variances, the greater is the F* ratio. On the contrary, the condition $F^{*} < F_{0.05}$ implies that the means are not significantly different and that the population, from which samples are drawn, cannot be substantially differentiated from each other.

3.2. ESTIMATION OF TEXTURAL FEATURES

It can be observed from the images of tea granules that the definite textural patterns contained in the images are characteristic of the sizes of tea granules and their colour. This fact was helpful in exploring the potential of computer vision based approach for characterizing the tea granules according to their grades. When the images of the tea granules are acquired, they are observed to contain stochastic natural textures. The tea grades have been sorted globally on the basis of their granule sizes and different granule sizes can be uniquely characterized by their textural features. The texture of tea granules has been a function of their size and a measure of uniformity throughout the image. If the image contains some granules of unexpected size or presence of granules of different grades, remarkable deviations can be observed in the textural features. In other words, a pure grade and a mixed grade tea samples would be having altogether different textural parameters. Thus, texture based sorting of granules can be presented as an alternate method of grading of tea granules. In the present section, a method for grading on the basis of textural parameters is presented.

3.2.1. Image Acquisition and Experimental Set-up

For estimation of textural features, black tea samples of four standard grades namely, leaf, brokens, fannings and dust were utilised for the experiments. The four standard graded samples having different grain size and shape were assigned the classes L, B, F and D. The procured standard samples of four diverse grades of tea were collected from tea manufacturing industries during the grading process and were duly graded by human experts.

A machine vision set up by and large has the following elements: lighting mechanism, a 3CCD colour camera (JAI-CV-M9-CL, National Instruments, Austin, TX, USA), an image capture board (National Instruments, PCI 1430e), computer hardware and software (Gill, *et.al.*, 2011; Wang & Sun, 2002). Performance of a computer vision system for a specific application greatly depends upon the way the system has been set-up. Shape, size and physical appearance of tea granules have been important attributes for differentiating them into different grades. Some important factors which must be taken into account for setting up the system for image acquisition are the distance and direction of view along with illumination. Any variations in either of these factors can result in large variations in system accuracy. For instance, the same object when viewed from different direction or distance could appear radically changed. Moreover, variation in viewing direction and illumination may result in either emphasising or obscuring certain surface features for the same sample of tea granules (Sarkar, 1991). Therefore, so as to maintain consistency, these factors were held constant during the entire image acquisition phase. The camera was kept perpendicular to the sample at a viewing distance of 135 mm. In addition to these issues, the way tea grains have been arranged in an image plays a significant aspect of the system performance. For estimation of textural features, bulk tea sample is spread uniformly over the imaging platform (Fig. 3.4) (Gill *et al.*, 2013). Overall surface uniformity is maintained for the arrangement of tea granules while imaging. Unlike the images for morphological feature estimation which were singulated in nature, the images for textural feature analysis are non singulated bulk images where tea granules touch and overlap each other.

3.2.2 Image database

For estimation of textural features of black tea, four image databases of different sized tea granules were considered in this experiment. From each graded sample of made black tea, a set of ten images were acquired and used for the experiment. Primary database comprised of sets of images designated L1-L10, B1-B10, F1-F10 and D1-D10 while the secondary database consisted of first order wavelet decomposed sub band images. To minimise the computational complexity of the technique, as a first pre-processing step, images were resized to maintain uniformity of samples (Gill *et al.*, 2013).

Leaf Brokens Fannings Dust

Figure 3.4: Acquired images for different tea grades

3.2.3 Textural Feature extraction

The preliminary assumption in characterization of texture was that significant facts regarding the textural profile of an image can be conveyed by GLCMs. GLCM provides an account of possibility of presence of two or more pixels having identical grey shade intensity in a specific orientation relative to each other in the image plane. When these pixels were repeatedly present in a defined orientation with respect to each other, they generated a definite textural profile. In case the texture was absent in an image, an absolutely diagonal GLCM is generated. This was frequently seen in solid images. When the textural variations increase, the values other than the diagonal ones assume significance.

Haralick (1973) quantitatively analyzed a number of textural attributes computed from GLCM (Wezka et. al., 1976; Wood, 1996; Al-Janobi, 2001; Rumelhart et. al., 1986). In the present work, six descriptors have been used (entropy, contrast, correlation, energy, homogeneity and mean) as textural attributes derived from the 40 GLCMs of database consisting of tea images. The textural features used in the experiment are elaborated in the following text.

Entropy in any system is an indicator of disorder and in field of texture investigation is an assessment of spatial disorderliness. It's a statistical gauge of the randomness of gray-level distribution. It is an important textural attribute that measures the arbitrariness which is used for characterizing the surface of an image and specified as:

$$\text{Entropy} = \sum_{i} \sum_{j} P(i,j)\log(P(i,j))$$

Entropy attains maximum value al the values in P are identical and this matrix corresponds to a situation where none of the desired gray values are present for any particular orientation with respect to each other. A totally randomized distribution generally has exceptionally elevated entropy as it signifies a total disorder. Entropy value for an image possessing solid tone would be 0. Entropy is a useful feature in conveying significant information regarding various types of textures.

Contrast quantifies the extent of localized variation in the GLCM generated from an image. It is considered to be dependence of grey values of adjoining picture elements in an image (Haralick *et.al.*, 1973).

$$\text{Contrast} = \sum_{n=0}^{N_{g-1}} n^2 \left\{ \sum_{i=1}^{N_g} P(i,j) \right\}$$

If the adjacent picture elements have similarity in their grey intensities, generally image contrast is on the lower side. In the analysis of texture, variations in the grey intensities depict a noticeable difference in textures. High contrast values characterize the heavy textures and low values are often an indicator for smooth and soft textures. The contrast is 0 for a constant image.

Correlation provides an estimate of grey scale linearly dependent picture elements present at the particular locations with respect to one another.

$$\text{Correlation} = \frac{\sum_{i} \sum_{j} (i,j)P(i,j) - \mu_x \mu_y}{\sigma_x \sigma_y}$$

A completely uniform image, the GLCM variance is 0 and, consequently, the denominator of the correlation equation is 0, thus making the correlation undefined.

Energy is a textural feature that presents the summation of squared entities of co-occurrence matrix. It is also referred as uniformity or the angular second moment. Energy quantifies local homogeneity and as a result it is completely opposed to Entropy. In other words, it is an indicator of how uniform the texture is

$$\text{Energy} = \sum \sum P^2 d(i, j)$$

The higher value of Energy value indicates the greater level of homogeneity of the texture. Energy is specified in the range of [0,1], where Energy equal to 1 represents a constant image.

Homogeneity provides an estimate as to how closely the entities of co-occurrence matrix are located with respect to its diagonal. It is an indicator of uniformness of non-zero values of co-occurrence matrix.

$$\text{Homogeneity} = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{P(i,j)^2}{R}$$

If homogeneity is on the higher side, it means that co-occurrence matrix has its values located around diagonal, i.e., a too many pixels are having comparable grey levels of intensities. Contrarily, lower GLCM homogeneity indicates large changes in grey levels thus resulting in higher contrast. The homogeneity is defined in the range [0,1]. Thus, high homogeneity points towards textures with recurring patterns, whereas lesser homogeneity points towards to large disparity in textural components as well as their locations. A non-homogeneous texture is the term that is often used for describing the images in which there is complete absence of repetition of textural elements and spatial resemblance.

Mean is a useful textural descriptor for describing homogeneous regions, at times it may not be able to provide substantial information regarding the disparity in the entities of co-occurrence matrix since various matrices can have similar values of this parameter and this similarity may lead to misleading interpretations.

$$\text{Mean} = \frac{1}{XY} \sum_{x=1}^{X} \sum_{y=1}^{Y} f(x, y)$$

The statistical features were computed for entire database of tea images for all four grades. The resulting feature value plots along with error bars were plotted. The image was further disintegrated by application of DWT (Fig. 3.5) (Gill *et. al*., 2011). The sub-bands obtained are designated as LH1, HL1, HH1 and LL1. While the first three represent the details, which were the fine scale components, the latter one represents approximations which were the coarse level coefficients. For further evaluation of next level of coefficients, the LL1 was subjected to decomposition (Fig. 3.5 (b)).

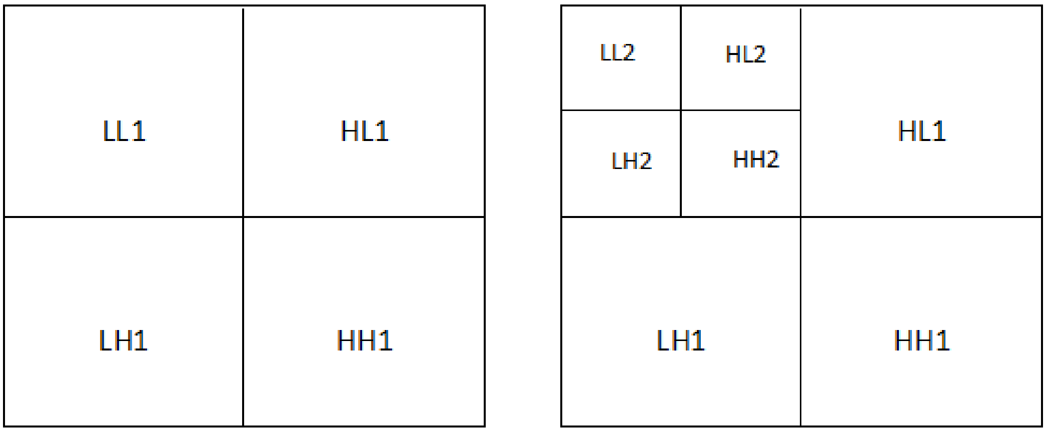


Figure 3.5: Image decomposition (a) Level - one (b) Level – two

Similarly, further decomposition could be carried out with LL2 and this procedure may continue till the desired scale was achieved. The coefficients estimated from the decomposed images serve as crucial attributes that can further be used for texture cataloguing. The values of textural attributes computed from the sub-band images distinctively portray a texture. For the current experiment, images were decomposed until the first level using the Daubechies wavelet base (Daubechies, 1988). Although various wavelet bases were available texture analysis, for the present application the Daubechies was preferred over other bases such as Haar and Gabor due to its ability to handle natural texture (Manian, 1998; Salari, 1995). The features extracted from the sub-bands exclusively characterise a texture. Six statistical attributes namely entropy, contrast, correlation, energy, homogeneity and mean were then computed again from the decomposed sub band LL1. Generally, LH1, HL1 and LL1 are discarded due to their low energy content and HH1 is employed for feature estimation. The band LL1 is used for further decomposition which was not carried out in this case.

The various statistical features extracted from wavelet decomposed sub-band images of made black tea along with error bars depicting 5% error are plotted to visualize the separation between various grades.

3.2.4 Data Classification

MLP classifier was used for training and cataloguing of dataset of textural features. The three layered MLP network was developed having 6 input, 18 hidden and an output neuron. LM backpropagation which update its connection weights values according to LM optimization has been used as training function. GDM is used as learning while MSE as performance function. MSE estimates the performance of MLP in accordance with mean-square-errors. The network is trained using these functions. The hyperbolic tangent sigmoidal transfer function is employed for hidden while linear function is employed for output layer neurons. The network returned classification efficiency of 87.5%. Further, when the same classifier when presented with the statistical features extracted from the level-one wavelet decomposed sub-band images, it retuned an improved classification accuracy of 100%.

3.2.5 Statistical Validation of Feature Data

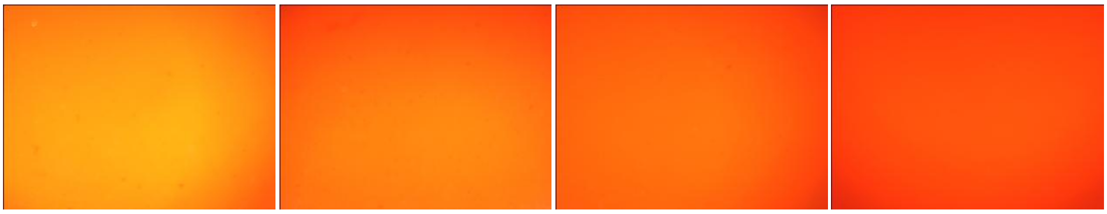
In order to validate the results statistically, ANOVA is applied to the database comprising of five statistical and five wavelet features. This method has been presented earlier in section 3.1.6.

3.3 ESTIMATION OF COLOUR FEATURES

Quality assessment of black tea has been done either at the tea industries before packing. Colour of tea liquor has been considered as one of the key parameters used to determine the grade of tea.

3.3.1. Image Acquisition and Experimental Set-up

The visual estimation of colour by the human sensory panel provides a reasonably accurate estimate in judgement of the colour. But, while imaging with the CCD cameras, a large numbers of parameters such as viewing distance, viewing angle and illumination condition play a very significant role. These parameters are generally adjusted by human operator as per his judgement and skill. In computer vision based system, if proper care is taken during imaging, it can enhance the system performance significantly. For instance, same colour might appear to be different during imaging if the direction of illumination, intensity of illumination or distance of image capturing is different (Gevers, *et. al.*, 1999). Although these parameters can be attuned to some extent by image pre-processing operations but maintaining identical set of conditions all through the imaging process is always beneficial. The imaging system comprised of a 3CCD colour camera (JAI-CV-M9-CL, National Instruments, Austin, TX, USA), an image capture board (National Instruments, PCI 1430e) along with associated computer hardware and software (Gill, *et.al.*, 2011; Wang & Sun, 2002). The camera was enclosed in aphotic housing and working distance was kept to be 135mm. For estimation of tea grades on the basis of colour, three grades of tea leaf, fannings and dust were evaluated. The captured images of brewed tea liquor for various grades are shown in fig. 3.6.



Leaf Brokens Fannings Dust

Figure 3.6: Acquired images of brewed liquor for different tea grades

3.3.2 Sample Preparation

The sample preparation for extracting colour information was prepared according to British Standard BS-6008. According to this standard, by weight 2 grams of tea is brewed per 100 ml of fresh boiling water for 6 minutes. The brewed liquor was then filtered and collected in a sample holder plate made up of clear glass. Borosil sample holder was used for this experiment

3.3.3 Colour Feature Extraction

The tea liquor was brewed for all four grades of black tea. An image database was generated and ten images were obtained for each grade of tea. The RGB colour model was preferred over other models in the current problem as RGB colour image is presumed to be composed of individual monochrome images of primary colours and due to this the computational complexity associated with evaluation of intensities is greatly reduced for the system based on RGB model. In addition to this, RGB colour scheme offers much bright compared to other models. Also more of the visible spectrum can be utilized with RGB scheme since it works on principle of transmission compared to reflection used by CMY. Further, RGB model being straight forward in nature is, typically, the most well suited model for hardware and software implementations. Though it has been criticised as incompatible with human perception, it matches well with human vision's strong response to primary colours. RGB was preferred choice for this work due to its computational simplicity and its hardware and software compatibility.

Extraction of the colour components or features is always a preliminary step in analysis and classification of colour images. In the simplest form, the colour content in an image can be represented by the pixel values in the red green and blue colour planes if an image is represented in RGB colour format. By definition, the notation followed for representing colour of a pixel is: ‘Pixel value = (R-level, G-level, B-level)’. Each pixel is allocated an integer value, in 0-255 range and, in all, a total of more than 16 million colours can be achieved with different combinations of these values.

The three colour features, namely, average R, average G and average B were computed from the image database for various grades of tea. These features correspond to the average colour content of the respective colour component in the image. The image in all compatible formats, having appropriate bit depth, can be used with the essential preliminary processing steps. True-colour image is transformed to greyscale image followed by resizing which imparts uniformity to the sample database. Further, the binary version of the image was created by changing greyscale image to a two tone image by selecting an appropriate threshold level. In the next step, colour analysis has been performed using RGB colour model. For estimation of the respective intensities of R, G and B components in an image the RGB colour model is preferred over HSI or CMY because RGB colour image can be segregated into set of constituent monochrome images. Due to this fact, the computational complexity associated with evaluation of intensities is greatly reduced for the system based on RGB model. Finally the mean of R intensity, G intensity, B intensity of each bulk image were extracted.

3.3.4 Feature Classification

It has been observed that various grades of black tea can be discriminated on colour based features and can be categorized into different grades by using ANN technique. In order to discriminate the grades on the basis of colour, MLP technique has been adopted.

***MLP structure and implementation*:** MLP has been employed as a classification tool for discrimination between the diverse grades of tea on the basis of colour features. The image database used for network training comprised of images of four diverse grades viz., leaf, brokens, fannings and dust. The MLP network was developed having three input layer neurons, two hidden layers having 14 and 13 neurons and an output layer. The training function used was the LM backpropagation (*trainlm*) which update its connection weights values according to LM optimization. GDM (*learngdm*) is used as learning while MSE as performance function. MSE estimates the performance of MLP in accordance with mean-square-errors. The network is trained using these functions. The hyperbolic tangent sigmoidal transfer function is employed for hidden while linear function is employed for output layer neurons. The network returned 80% correct classifications for the feature data base.

3.3.5 Statistical Validation of Feature Data

In order to statistically validate the results, ANOVA is applied to database comprising three features *viz.* average R, average G and average B. This method has been presented earlier in section 3.1.6.

3.4 ESTIMATION OF MOISTURE

Moisture measurement was carried out for all four grades of tea by thermogravimetric analysis (TGA). TGA is well known technique used for measurement of the changes in sample mass when heated. In addition to estimation of moisture in the sample, TGA can also provide other analytical possibilities like detection of substance constituents along with the information regarding the thermal and oxidative stability of the material. TGA instruments are have an in-built precision thermo-balance within the heating chamber that continuously measures and records weight variations taking place in sample mass all through the predefined heating schedule (Nollet and Toldra, 2015).

Moisture determination procedure using thermogravimetric analyzer comprises of holding a specific quantity of sample in a sample holder and choosing an appropriate heating format, i.e., planning the temperature, gradient, flow rate and pressure of the gas used. Moisture is continually removed from sample, by evaporation, till a steady value of mass is arrived at (Nollet and Toldra, 2015). Perkin Elmer Diamond TG/DTA was used for estimation of moisture of four different grades of black tea. Temperature was set at 200°C, with sample of 10mg and a heating rate of 10°C/min. The moisture content was measured as difference of weight of sample before TGA analysis and after it as at upon heating the sample to 100°C moisture evaporates from the sample completely.

3.5 ESTIMATION OF DENSITY

The bulk density of tea granules has been another useful physical parameter that can provide useful information about the tea grade as the tea granules for different grades of black tea differ in shape and size and they have a different packing density. The bulk density of tea granules was estimated for tea granules of all four grades in two different modes i.e. compacted and un-compacted. While the un-compacted density is defined as the ratio between the mass of a substance in un- compacted form and the volume of same substance along with the share occupied by voids, the compacted density is the enhanced density that is obtained when mechanical vibrations are used to shake the sample holder with the sample inside it.

Apparatus used for this method consisted of a fixed volume cylinder having total volume of 13.47cm^3. Before carrying out the experiment, the mass of empty container is measured. The sample was poured into the cylinder. An excess of tea leaves are poured into the cylindrical container until it overflows. The excess portion was, then, carefully scraped from the top of the container. The container was then placed on an analytical balance and the mass of the container containing the tea leaves was measured. Now, from this observation, the mass of empty container was subtracted and the resultant value of mass was divided by the volume of the container. This value corresponds to the un-compacted density of the sample under observation. Further, the sample was tapped and upon compaction, the level of granules in container drops down. The drop in level was measured and the volume occupied by the same mass of tea granules was measured and compacted density is computed from this. Same procedure for estimation of compacted and un-compacted densities for all four grades of tea was carried out.

CHAPTER 4
RESULTS AND DISCUSSION

4.1 GRADING BASED ON MORPHOLOGICAL FEATURES

The morphological features namely area, perimeter and aspect ratio were computed for four grades of tea. For this purpose, a database of tea images, 8 for each grade were used. These images were captured in identical situations and the samples for each of the eight images belonging to the same grade were drawn randomly from the same population. The fundamental reason of using more than one image for same grade was to get an averaging effect about the measured parameters. A coin of rupees two denomination was used as a reference for calibrating the pixel values returned by the measurement into the physical units. The area has been expressed in mm^2, perimeter as mm and aspect ratio is dimensionless. The computed values of area, perimeter and the aspect ratio have been tabulated in Table 4.1 for all four grades of black tea namely, leaf, brokens, fannings and dust.

From the data, it was clearly evident that the size of granules belonging to grade 'Leaf' was the maximum of all the four grades. The area for this grade ranged from 23.74 mm^2 to 29.35 mm^2 while the perimeter ranged from 4.78 mm to 5.15 mm. This grade clearly stands out from the other three grades by virtue of its area and perimeter. Moreover, the range for aspect ratio for this grade was from 1.33 to 1.63, which indicated that the granules for this grade were not circular in nature compared to the rest three grades where the aspect ratios were in the range of 0.78-1.32. The area and perimeter for brokens closely followed the Leaf although there was no significant overlap in their size and perimeter. Both leaf and brokens were considerably large in size compared to fannings and dust. Aspect ratio proved to be a key parameter in discriminating between the leaf and brokens as unlike the leaf, the brokens were nearly circular in shape with the aspect ratio of around unity. Fannings are next in size to brokens and the dust follows them. The ranges for area, perimeter and aspect ratios for all four grades of tea have been summarized in Table 4.2. From the graphical representation of area (Fig. 4.1) for different types of tea, it was clearly evident that all four grades stood apart from each other. Here, the first 8 bars represent the values of area for grade 'leaf' and they represent the average areas that have been computed from the eight images that were captured for this grade while the subsequent sets of eight bars each, represent the average area values of brokens, fannings and dust. Similarly, from the graphical representation for perimeter, a crisp distinction between the various grades can be made.

Table 4.1: Computed Morphological features for various grades of Black Tea

Area (in mm^2)	Perimeter (in mm)	Aspect Ratio
Leaf		
29.35	5.15	1.44
24.84	5.15	1.51
29.44	5.15	1.43
25.48	4.78	1.51
29.39	5.24	1.43
23.74	4.97	1.37
24.38	4.97	1.33
24.52	5.06	1.63
Brokens		
21.2	4.42	1.15
23.03	4.51	0.93
21.34	4.42	1.2
20.63	4.61	1.28
22.89	4.61	1.29
23.55	4.51	1.07
22.98	4.51	1.08
23.17	4.61	1.08
Fannings		
8.06	2.59	1.19
8.26	2.59	1.29
8.16	2.59	1.14
7.25	2.4	1.29
8.11	2.59	1.23
8.16	2.59	1.31
7.97	2.59	1.2
8.06	2.59	1.2
Dust		
3.15	0.99	1.19
2.25	1.08	1.32
1.35	0.81	0.98
1.13	0.72	1.11
2.84	1.26	0.78
3.24	1.35	1.13
2.88	1.26	1.01
1.8	1.08	1.19

Table 4.2: Area, Perimeter and Aspect Ratios for various grades of Black Tea

Grade	Area (in mm.^{2})	Perimeter (in mm.)	Aspect Ratio
Leaf	23.74-29.35	4.78-5.15	1.33-1.63
Brokens	20.63-23.55	4.42-4.61	0.93-1.29
Fannings	7.25-8.26	2.40-2.59	1.2-1.31
Dust	1.13-3.24	0.72-1.35	0.78-1.32

However, from the values of aspect ratio, 'leaf' grade can be differentiated from the rest four grades but the other three grades have an overlap for this parameter. The values of all computed morphological features along with error bars depicting the percentage error of 5% have been shown in Figs. 4.1-4.3.

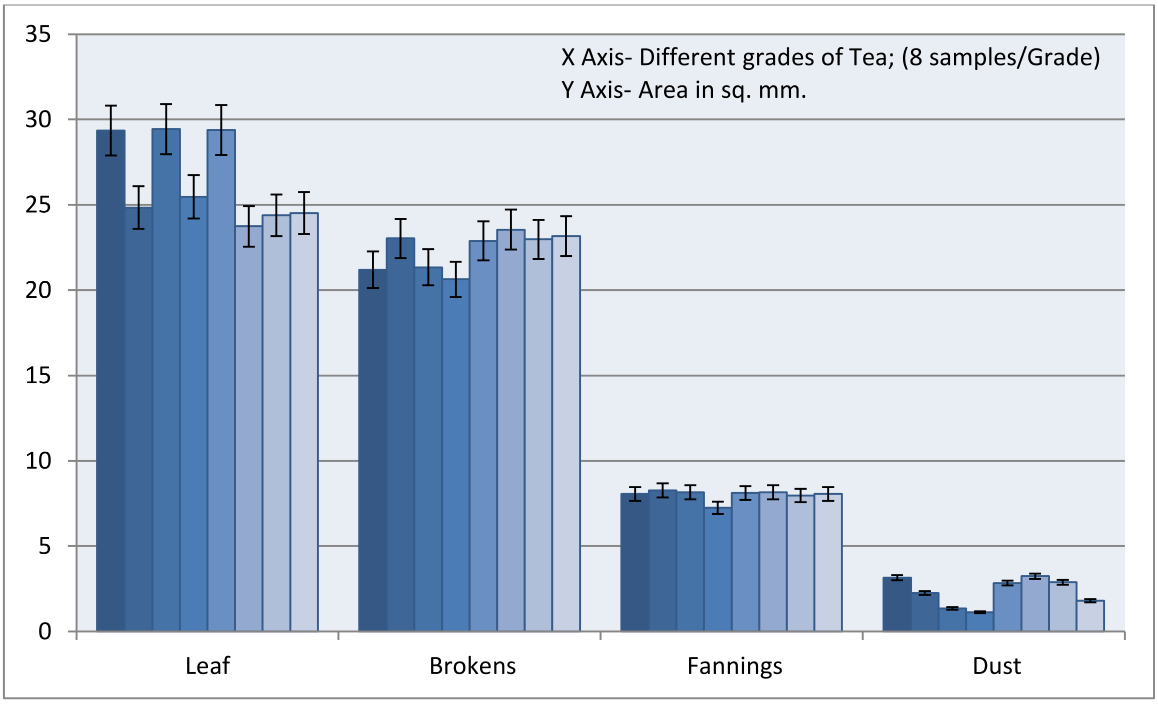


Figure 4.1: Area plots for various grades of tea

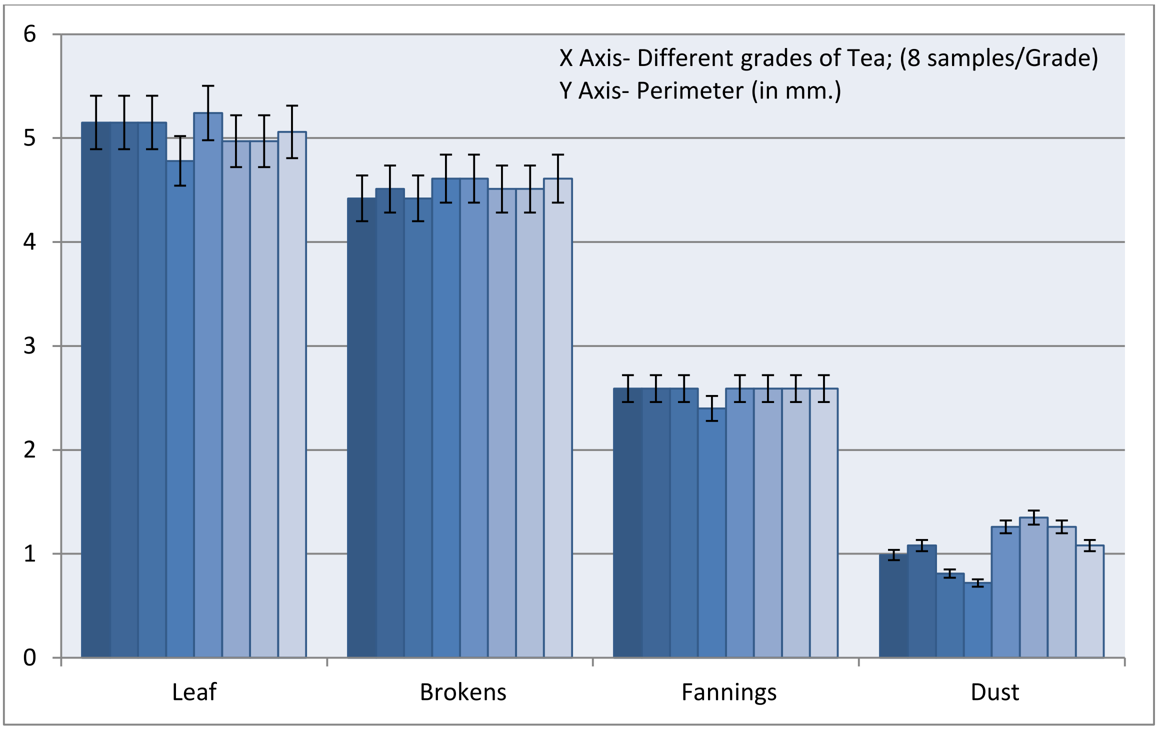


Figure 4.2: Perimeter plots for various grades of tea

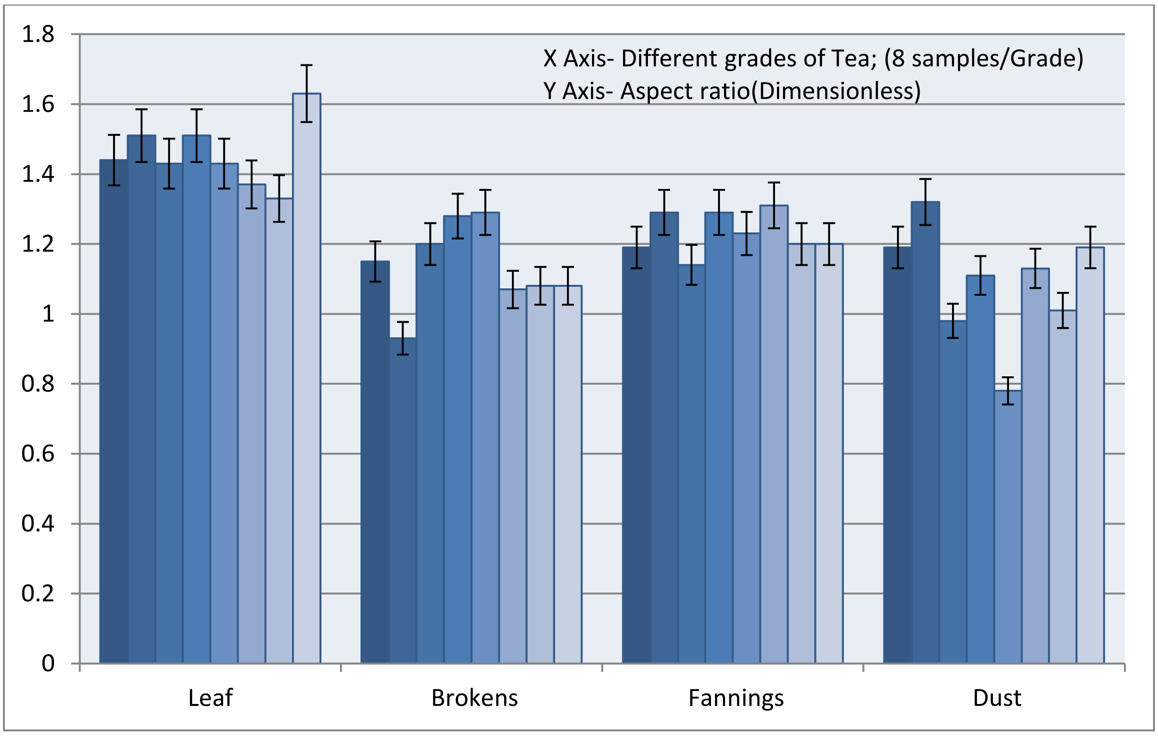


Figure 4.3: Aspect-ratio plots for various grades of tea

The error bars are the indicators of uncertainty or a measure of inaccuracy for a particular data point. The error bars shown in the bar graphs (Figs. 4.1-4.3) symbolize an account of assurance the value correspond to an accurate value the feature area. The higher the range of the measured value above and below the average value, the more were the length of those particular error bars and lesser the confidence about that value. Observing the error bars to the distribution measured values of area (Fig. 4.1), it could be observed that the tight distribution of area values in case of fannings and dust results in small error bars while the loose distribution of points in case of leaf and brokens results in more pronounced error bars. Precisely, the section of bar atop each point stands for +1 standard error and that below it signifies -1standard error.

For classifying the data based on morphological features, multilayer perceptron architecture has been used with one hidden layer having 28 neurons. The screen shot for ANN classifier has been presented in Fig. 4.4 and the performance plot in Fig. 4.5. The best validation performance of 0.0081654 was obtained in the third epoch. In general, more the training session epochs, lesser was the error, but, at times, due to over-fitting issues during training, it may tend to increase. However, by default, MATLAB ANN toolbox discontinues training for more than 6 validation checks when the minimum gradient was achieved as in present case. The top performance corresponds to the epoch having least validating error which was given by the third epoch in the present case. The network returned 100% correct classification for data with no incorrect classifications. **The confusion matrix in this case was** 100% accurate. The diagonal elements of confusion matrix represent correct classifications while the remaining elements represent incorrect responses (Fig. 4.6).

Performance plot shows the MSE dynamics for the datasets on logarithmic scale. Since the training MSE is observed to be declining, so its validation as well as testing MSE was of principal importance. The plot in this case demonstrated perfect training. **Training state** also shows some other training statistics as well. Gradient is the value of back-propagation for each iteration on logarithmic scale. Gradient value of 5.43e-12 meant that network had attained local minima of the goal function. Validation checks were the iterations when validation MSE increased its value. More number of validation checks indicates over training.

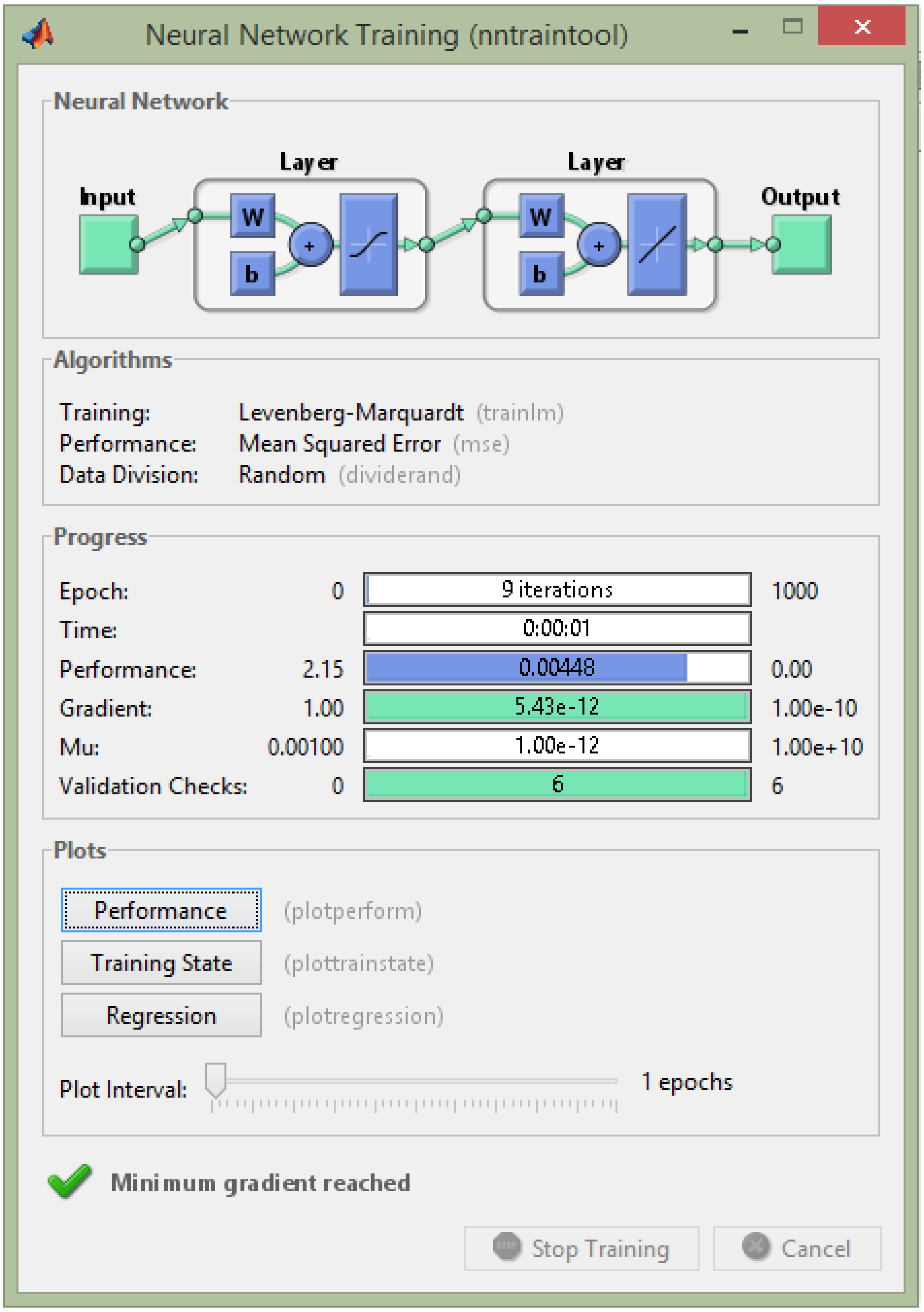


Figure 4.4: ANN classifier for Morphological parameters (using MATLAB)

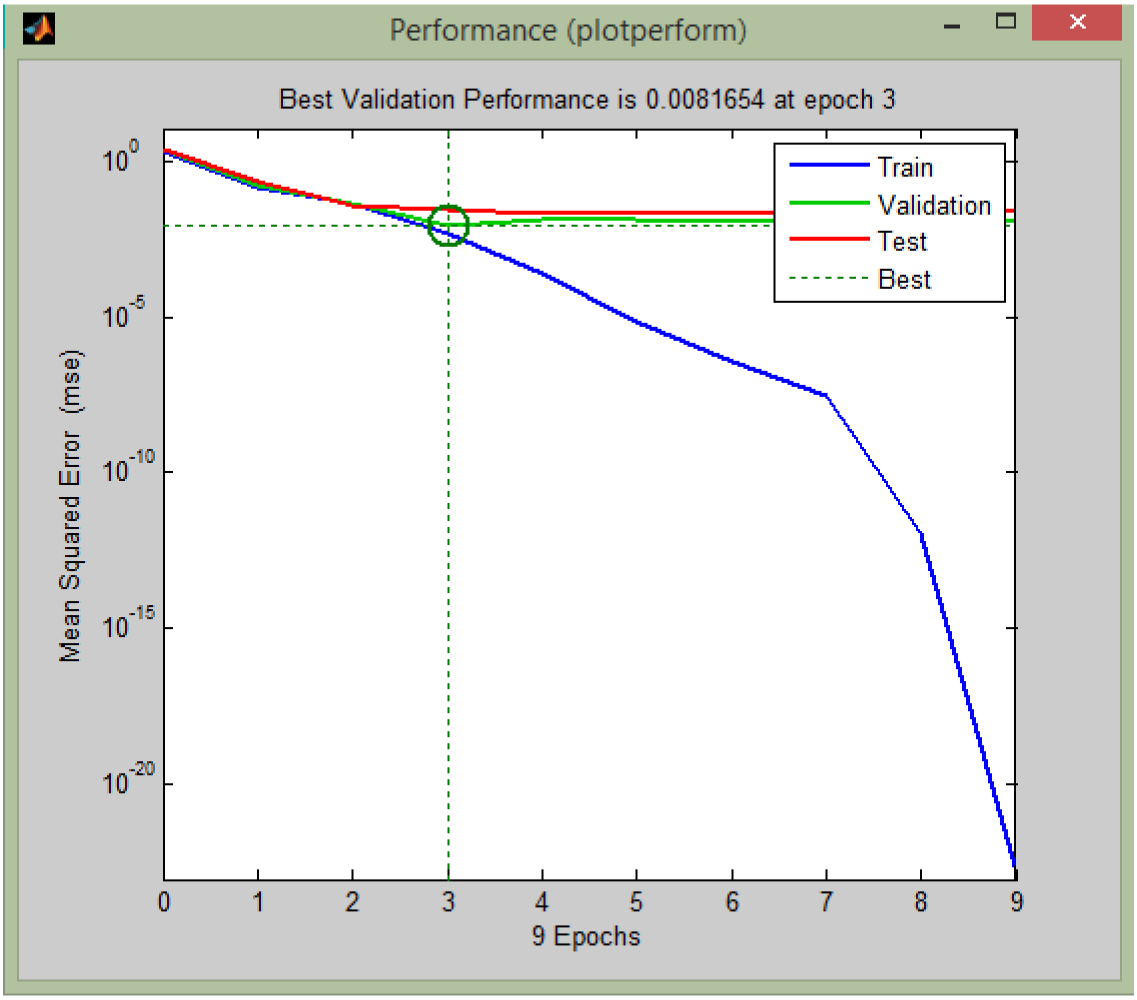


Figure 4.5: Performance plot of the ANN Classifier for Morphological Parameters

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13/9/15 3:51 PM                    MATLAB Command Window

Total testing samples: 6

cm =

     0     0     0     0
     0     2     0     0
     0     0     2     0
     0     0     0     2

Percentage Correct classification   : 100.000000%
Percentage Incorrect classification : 0.000000%
```

Figure 4.6: Confusion Matrix for Morphological Parameters

The next step in validating the network was the creation of a regression plot (Fig 4.7), which shows the relationship between the outputs of the network and the targets. If the training was perfect, the network outputs and the targets should be exactly equal, but in practice, this relationship has been rarely perfect. The four plots represent the training, validation, testing and overall data. The dashed line in each plot represents the perfect result where the outputs are equal to targets. The solid line represents the best fit linear regression line between outputs and targets. The R value signifies the liaison amongst the output and target. If R = 1, this indicates that there has been an exact linear relationship between outputs and targets. The R value close to zero indicates that there was no linear relationship between outputs and targets. For the current work, the training data indicates an excellent fit. The validation and test results also show R values greater than 0.9.

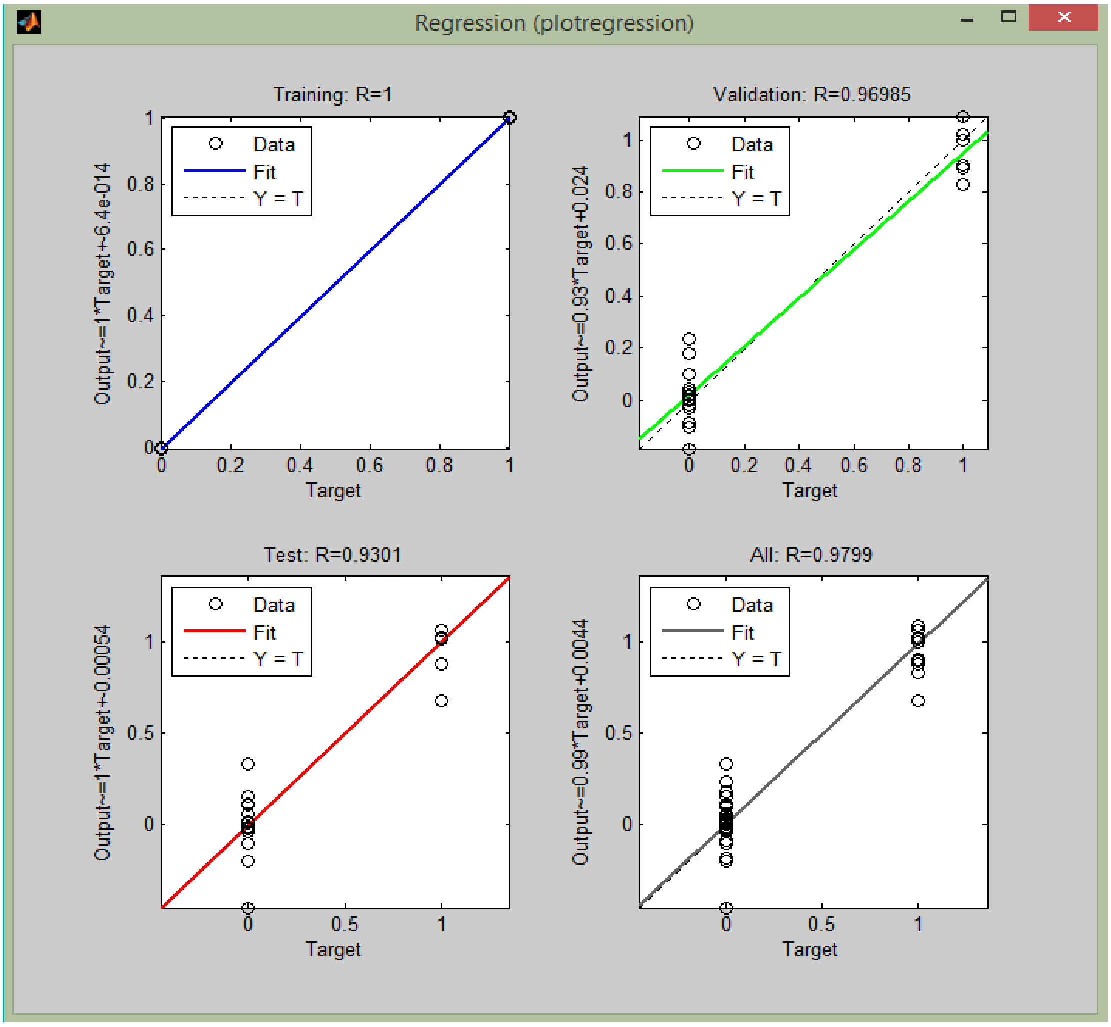

Figure 4.7: Regression plot of the ANN Classifier for Morphological Parameters

Further, statistical analysis was carried out by one-way analysis of variance (ANOVA). ANOVA is a way to test the equality of three or more means at one time by using variances. The feature data from image analysis were examined for the diverse grades of tea to establish whether different grades of processed black tea were statistically different from one another. The features for all grades were analysed using ANOVA. Variance ratio (F*) was computed for each feature set and the actual value was weighed against with tabulated at 5% significance scale (Koutsoyiannis, 2001). The measured and tabulated values of F for various features have been given in Table 4.3. A high F value can be found when the means for all of the groups differ at least moderately from each other, as in case of area and perimeter. As a general rule, larger the difference among the variance values, higher is the F* ratio.

Table 4.3: ANOVA results for Morphological features

Feature	Observed Variance Ratio (F*)	Theoretical Variance Ratio ($F_{0.05}$)
Area	623.15	2.84
Perimeter	1642.39	2.84
Aspect Ratio	19.82	2.84

F*-Estimated (observed) variance ratio; $F_{0.05}$= theoretical value of at 5% level of significance

It can be observed that for all three morphological features viz., area, perimeter and aspect ratio the observed values (F*) were greater than theoretical values (F) i.e. $F^* > F_{0.05}$. This implies that the differences between means were significant and the populations, from which the samples were drawn, vary considerably from one another (Table 4.3). Hence, the ANOVA illustrated that the selected attributes were well suited to distinguish amongst the tea grades.

4.1 GRADING BASED ON TEXTURAL FEATURES

The textural features namely, energy, entropy, contrast, correlation and homogeneity were computed for four grades of tea (Table 4.4). For this purpose, a database of tea images comprising of ten images for each grade was utilized. These images were captured under identical set of conditions and the samples for each of the ten images belonging to the same grade were drawn randomly from the same population. The fundamental reason of using more than one image for same grade was to get an averaging effect about the measured parameters.

Table 4.4: Textural features (Statistical) for various grades of Black Tea

Grade	Entropy	Contrast	Correlation	Energy	Homogeneity
LEAF	7.5286	7.4689	0.096	0.0198	0.4724
	7.2489	7.1617	0.089	0.0222	0.4716
	7.2456	6.9539	0.1204	0.021	0.477
	7.2058	7.2901	0.0979	0.0206	0.4725
	7.1071	6.7511	0.0949	0.0247	0.4878
	7.2364	7.0989	0.0897	0.0218	0.476
	7.1726	6.5866	0.0918	0.0234	0.4849
	7.2319	6.3622	0.1152	0.0221	0.4871
	7.2244	7.2944	0.0903	0.0219	0.4711
	7.1709	7.5152	0.0938	0.0224	0.4748
BROKENS	6.3623	4.6573	0.1666	0.0466	0.5344
	6.3532	4.4801	0.1729	0.0479	0.539
	6.3023	4.0458	0.1494	0.0585	0.5579
	6.3582	4.2192	0.1615	0.0526	0.5533
	6.318	4.4893	0.1435	0.0551	0.5508
	6.3548	4.3885	0.1297	0.0611	0.5585
	6.3813	4.2673	0.1422	0.0602	0.5556
	6.3311	4.2994	0.1636	0.05	0.5415
	6.3367	4.5312	0.1578	0.0486	0.5389
	6.3397	4.5716	0.1357	0.0546	0.5521
FANNINGS	6.8994	5.5552	0.0784	0.0355	0.5047
	6.8289	5.8355	0.0881	0.0421	0.5149
	6.8518	5.4463	0.1006	0.0355	0.5073
	6.8225	5.3837	0.092	0.0366	0.5088
	6.8442	5.3677	0.0876	0.0351	0.4994
	6.829	5.5528	0.0963	0.0412	0.5133
	6.8022	5.332	0.0993	0.0371	0.5112
	6.8062	5.7776	0.076	0.0358	0.4996
	6.7878	5.1396	0.102	0.0452	0.5268
	6.8006	5.4434	0.0941	0.0405	0.5159
DUST	6.9173	5.8013	0.0991	0.0368	0.5114
	6.8917	5.6952	0.1014	0.0365	0.5115
	6.9269	5.5972	0.1079	0.037	0.5153
	6.8927	5.3418	0.1199	0.0371	0.5171
	6.8613	5.8047	0.0973	0.0372	0.5122
	6.904	5.7286	0.0907	0.0331	0.503
	6.8825	5.3874	0.0872	0.0486	0.5287
	6.9212	5.3247	0.106	0.038	0.5123
	6.9057	5.3731	0.1062	0.0427	0.5226
	6.8587	5.3226	0.1183	0.0427	0.5255

The graphical representations of textural features depicting 5% error are presented in Figs. 4.8 - 4.12. The error bars are used for statistically describing the uncertainty in the measurements. They symbolize a portrayal of the assurance that measured value correspond to true value for a particular feature. The more the original data values range above and below the mean, the wider the error bars and less confident one is about a particular value. For instance, consider the case for brokens in plot for feature 'contrast' (Fig. 4.9). The shorter error bars signify the higher level of confidence in that value. Moreover, the shorter error bars convey a tight distribution of the particular feature for brokens. Similar is the case for grade 'leaf' in correlation (Fig. 4.10) and energy (Fig. 4.11) plots where again short error bars indicate relatively tight distribution with high confidence level.

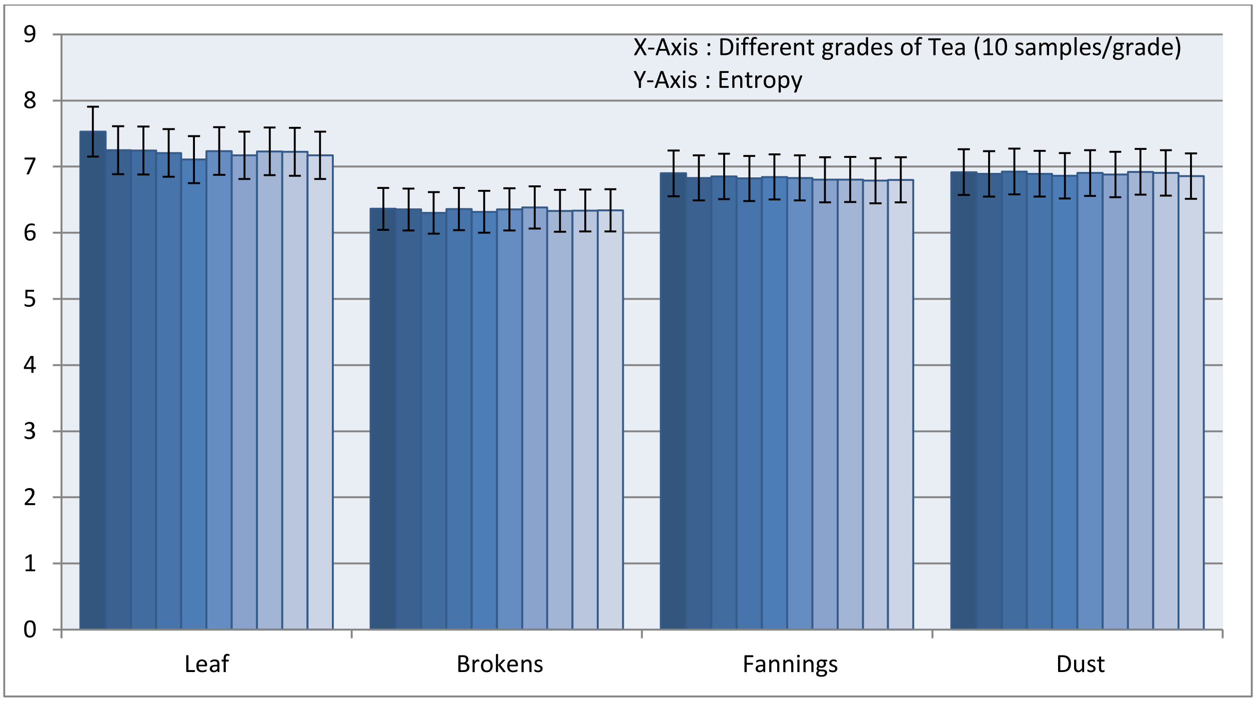

Figure 4.8: Entropy plots for various grades of tea

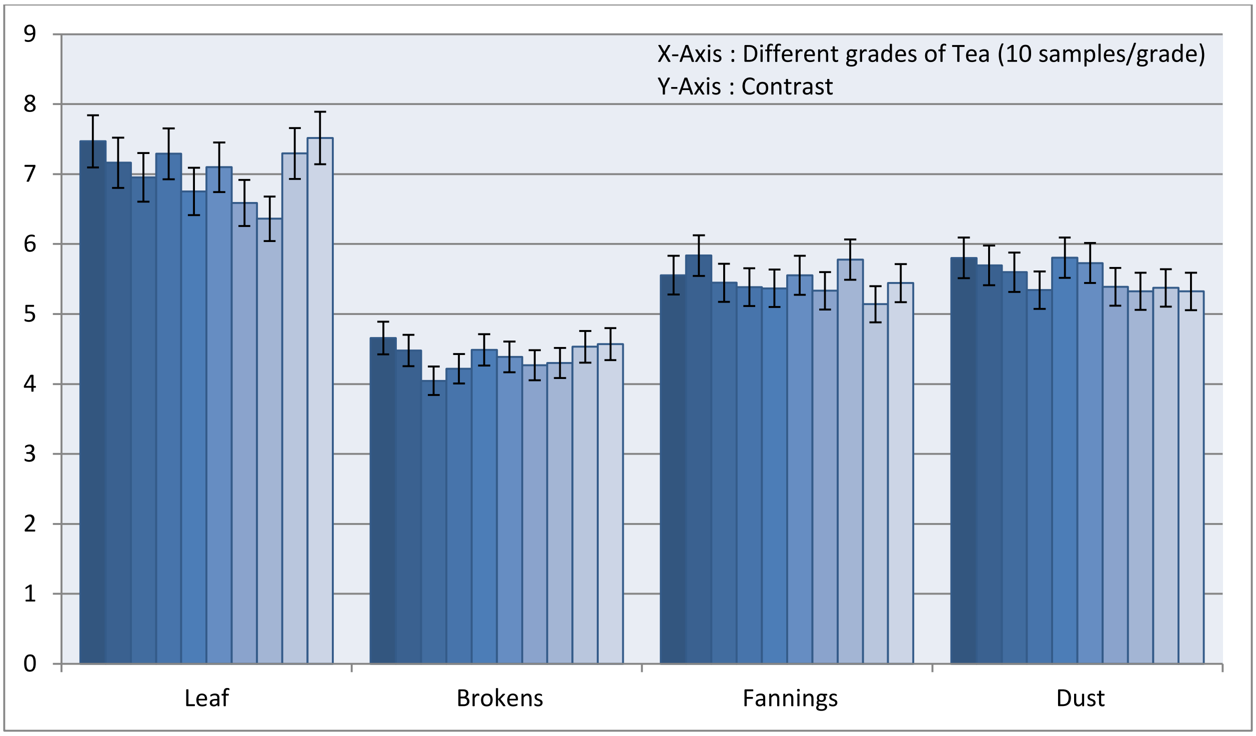

Figure 4.9: Contrast plots for various grades of tea

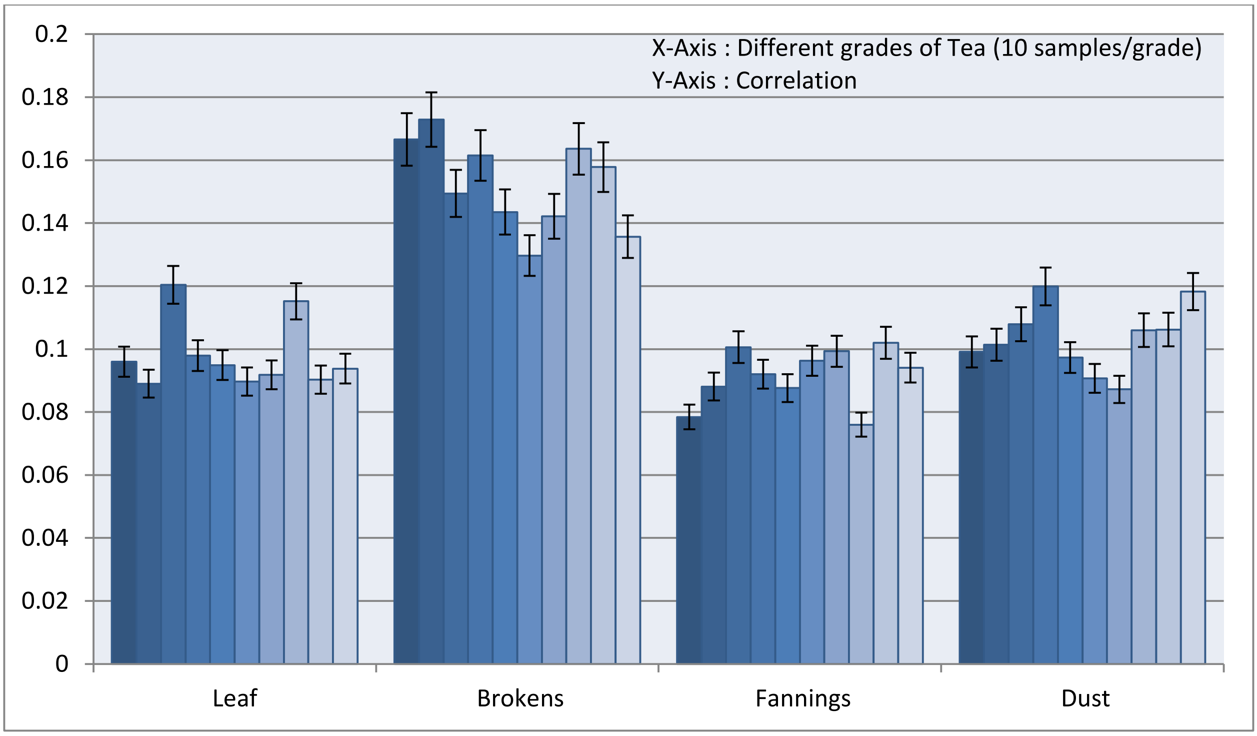

Figure 4.10: Correlation plots for various grades of tea

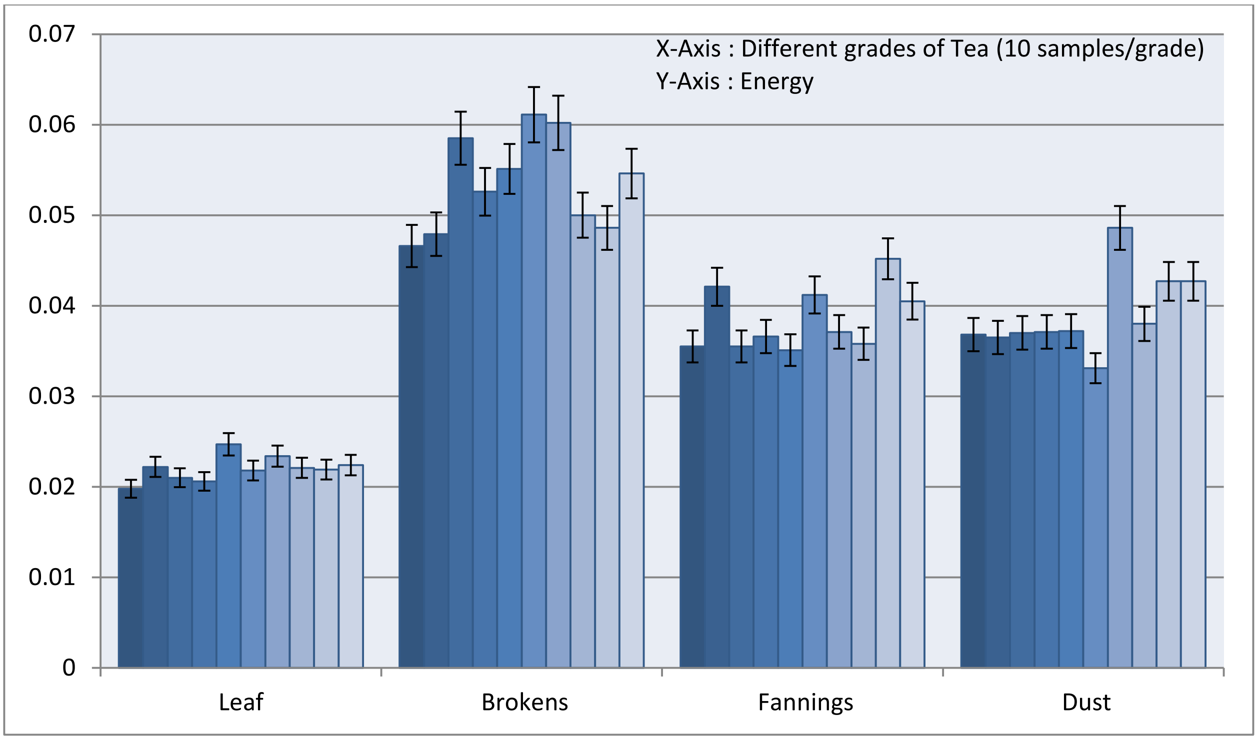

Figure 4.11: Energy plots for various grades of tea

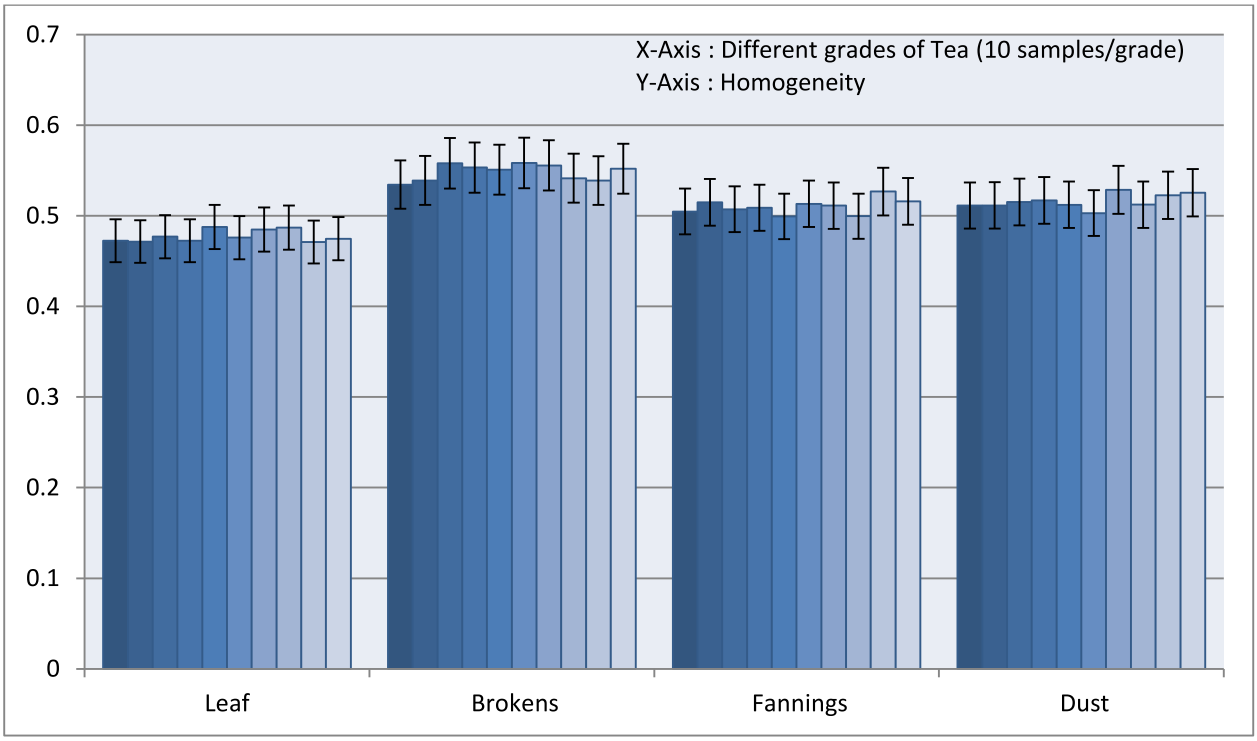

Figure 4.12: Homogeneity plots for various grades of tea

For classifying the data based on textural features, multilayer perceptron architecture has been used with one hidden layer having 18 neurons. The screen shot for ANN classifier is presented in Fig. 4.13 and the performance plot in Fig. 4.14. The best validation performance of 0.0625 was obtained in the 28th epoch. The network returned 87.5% correct classification for data with 12.5% incorrect classifications. **The confusion matrix in this case is** 87.5% accurate (Fig. 4.15). **Performance plot** shows the mean square error dynamics for the datasets on logarithmic scale.

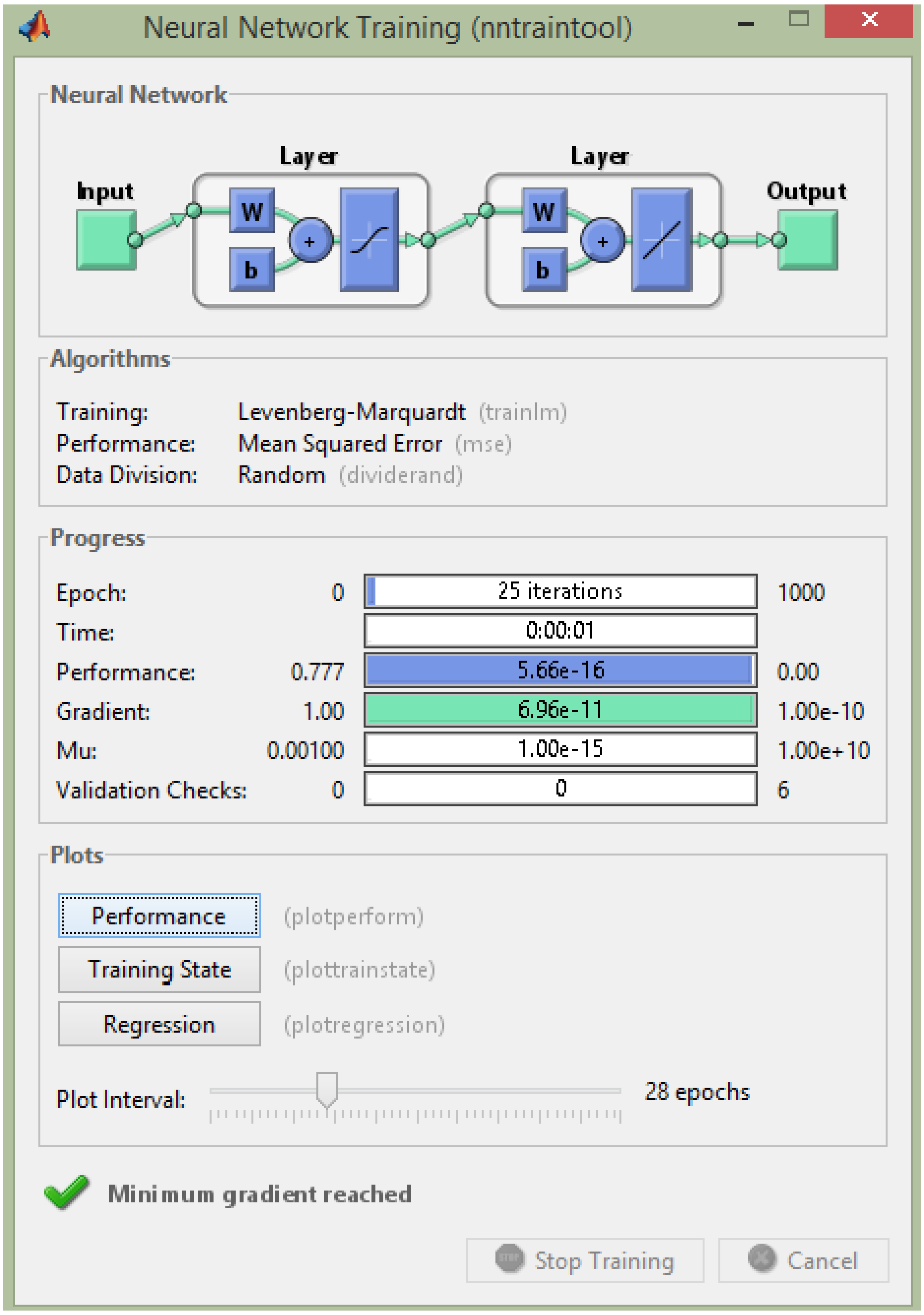

Figure 4.13: ANN classifier for Textural parameters (using MATLAB)

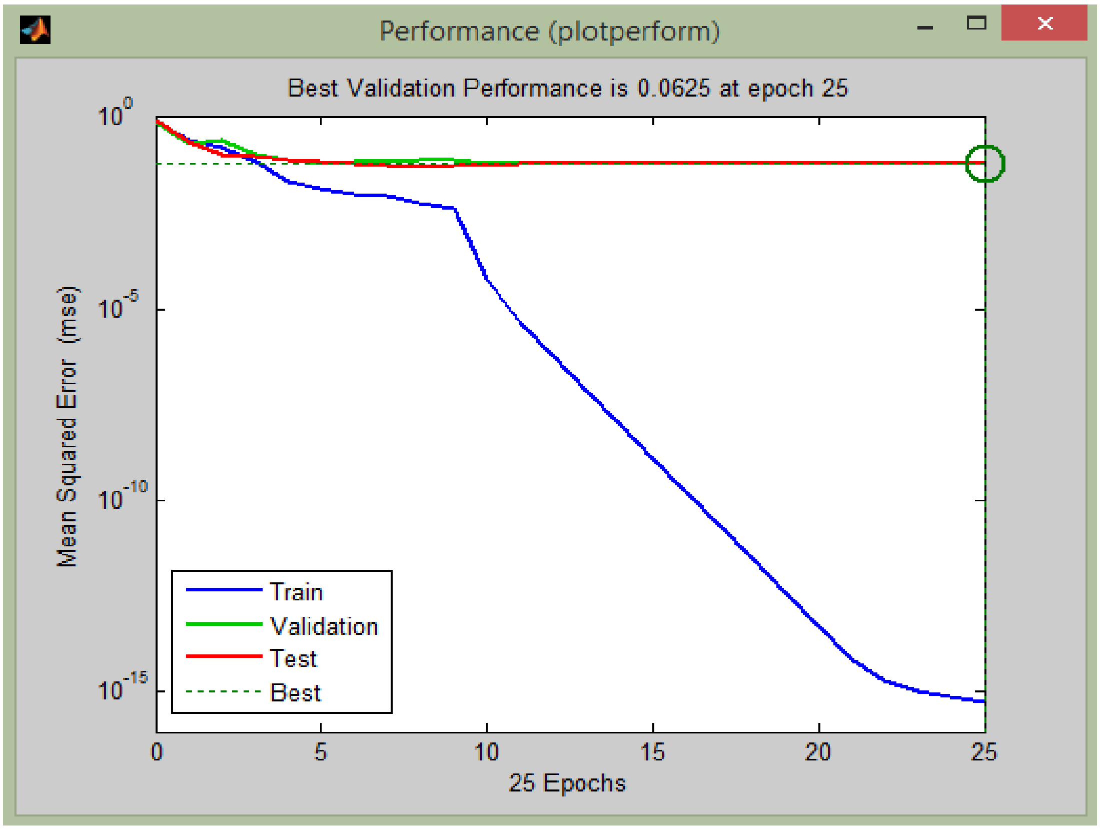

Figure 4.14: Performance plot of the ANN Classifier for Textural Parameters

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13/9/15 11:20 PM                MATLAB Command Window

Total testing samples: 8

cm =

     0     0     0     0
     0     2     0     0
     0     0     3     1
     0     0     0     2

Percentage Correct classification   : 87.500000%
Percentage Incorrect classification : 12.500000%
```

Figure 4.15: Confusion Matrix for Textural Parameters

Since the training MSE is showing a decreasing trend, so the validation and test MSE are the ones that have to be observed. The plot in this case shows a perfect training. Gradient value of 6.96e-11 indicates that the network has reached the bottom of local minimum of the goal function without any validation check.

Further, regression plot (Fig 4.16) indicates perfect training with R=1, i.e., the network outputs and the targets are exactly equal, though, practically this relationship is rarely perfect. The four plots represent the training, validation, testing and overall data. The dashed line in each plot represents the perfect result where the outputs are equal to targets, while the solid line represents the best fit linear regression line between outputs and targets. For the textural feature set, the validation and test results also show regression coefficient of 0.83333 and 0.83087, respectively.

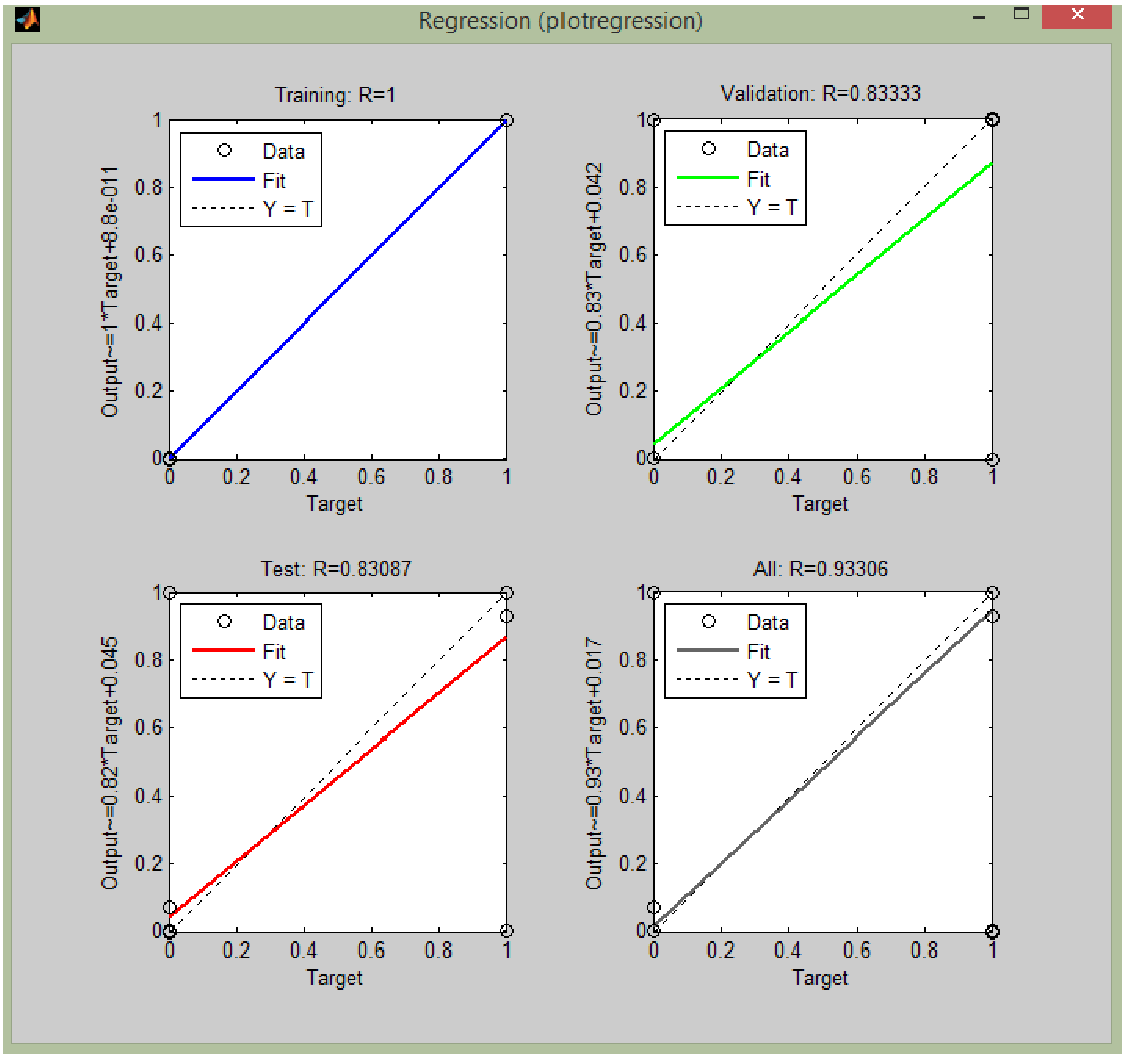

Figure 4.16: Regression plot of the ANN Classifier for Textural Parameters

Finally, statistical analysis is carried out by one-way analysis of variance (ANOVA) in which all the five textural features have $F^* > F_{0.05}$ which indicates that the diverse grades can be considerably categorized on account of each of the textural parameters (Table 4.5). However, entropy proved to be the best one out of the all five followed by contrast that was closely followed by energy and homogeneity.

Table 4.5: ANOVA results for Textural features

Feature	Observed Variance Ratio (F*)	Theoretical Variance Ratio ($F_{0.05}$)
Entropy	395.61	2.84
Contrast	203.48	2.84
Correlation	59.32	2.84
Energy	167.79	2.84
Homogeneity	167.44	2.84

F*-Estimated (observed) variance ratio; $F_{0.05}$= theoretical value of at 5% level of significance

In order to improve the results for textural images, the image is decomposed i.e., divided into four sub-bands by applying discrete wavelet transform (DWT) as shown in Fig. 3.5 (a) (Gill et al., 2011). In order to obtain next coarse level of wavelet coefficients, LL1 is further disintegrated (Fig. 3.5 (b)). For the present work, images were decomposed until the first level using the Daubechies wavelet base (Daubechies, 1988). Five textural features as computed above were again computed for the wavelet sub-band image (Table 4.6) and graphically represented with 5% error bars in figs. 4.17-4.21. It is evident from these plots that relatively pronounced error bars for energy1 and homogeneity1 indicate the loosely distributed data with low level of confidence in their values compared to the other three features.

The classifier used in this case is an MLP with 20 neurons in hidden layer (Fig 4.22) which gives the best validation performance of 6.46e-15 in the 5th epoch. The network returned 100% correct thus improvising the results obtained from statistical textural attributes mentioned above. **The confusion matrix for eight test inputs also gives 100%** accuracy (Fig. 4.24). **From the performance plot, it can be observed that** training MSE is shows a decreasing trend and this indicates a good training, while the validation and test curves are almost overlapping each other, which is a desirable aspect (Fig. 4.23). Gradient value of

0.31493 indicates that the network has reached the bottom of local minimum of the goal function, and that too, without any validation check.

Table 4.6: Textural features (DWT) for various grades of Black Tea

Grade	Entropy1	Contrast1	Correlation1	Energy1	Homogeneity1
LEAF	0.098	0.519	0.4702	0.9699	0.9906
	0.0917	0.4488	0.5055	0.9731	0.9919
	0.096	0.4693	0.5014	0.9717	0.9915
	0.0905	0.4417	0.488	0.9739	0.992
	0.0887	0.4117	0.5113	0.975	0.9925
	0.0958	0.4881	0.4842	0.9711	0.9912
	0.0973	0.5108	0.4692	0.9703	0.9907
	0.0945	0.4346	0.5126	0.9731	0.992
	0.0922	0.4682	0.4799	0.9726	0.9915
	0.0903	0.4298	0.5121	0.974	0.9923
BROKENS	0.0895	0.4152	0.5014	0.9747	0.9924
	0.0896	0.4355	0.4877	0.9742	0.9932
	0.0837	0.376	0.5289	0.9768	0.9932
	0.0833	0.4092	0.5029	0.9754	0.9925
	0.0855	0.3735	0.53	0.9767	0.9931
	0.0815	0.3539	0.5463	0.9779	0.9936
	0.0827	0.353	0.5453	0.9778	0.9936
	0.0928	0.4619	0.4695	0.9728	0.9915
	0.0921	0.4578	0.4705	0.9731	0.9916
	0.0837	0.3573	0.5449	0.9775	0.9935
FANNINGS	0.0857	0.4004	0.5108	0.9758	0.9927
	0.0829	0.3642	0.5408	0.9773	0.9934
	0.091	0.4569	0.4769	0.9733	0.9917
	0.087	0.4142	0.4984	0.9752	0.9925
	0.0875	0.3985	0.5129	0.9757	0.9927
	0.0836	0.3868	0.5198	0.9766	0.9931
	0.0826	0.3552	0.5452	0.9776	0.9936
	0.0846	0.3571	0.5493	0.9772	0.9935
	0.0849	0.3734	0.5311	0.9768	0.9932
	0.0826	0.3608	0.5419	0.9775	0.9935
DUST	0.084	0.3864	0.5236	0.9765	0.9931
	0.0832	0.3475	0.557	0.9778	0.9937
	0.0847	0.3676	0.5401	0.977	0.9933
	0.0842	0.3692	0.5335	0.9771	0.9933
	0.0825	0.3667	0.5358	0.9773	0.9934
	0.0835	0.3736	0.5332	0.9769	0.9933
	0.0796	0.3228	0.5788	0.979	0.9942
	0.0851	0.391	0.5189	0.9762	0.9929
	0.0839	0.3608	0.5425	0.9775	0.9934
	0.0835	0.3489	0.5523	0.9777	0.9936

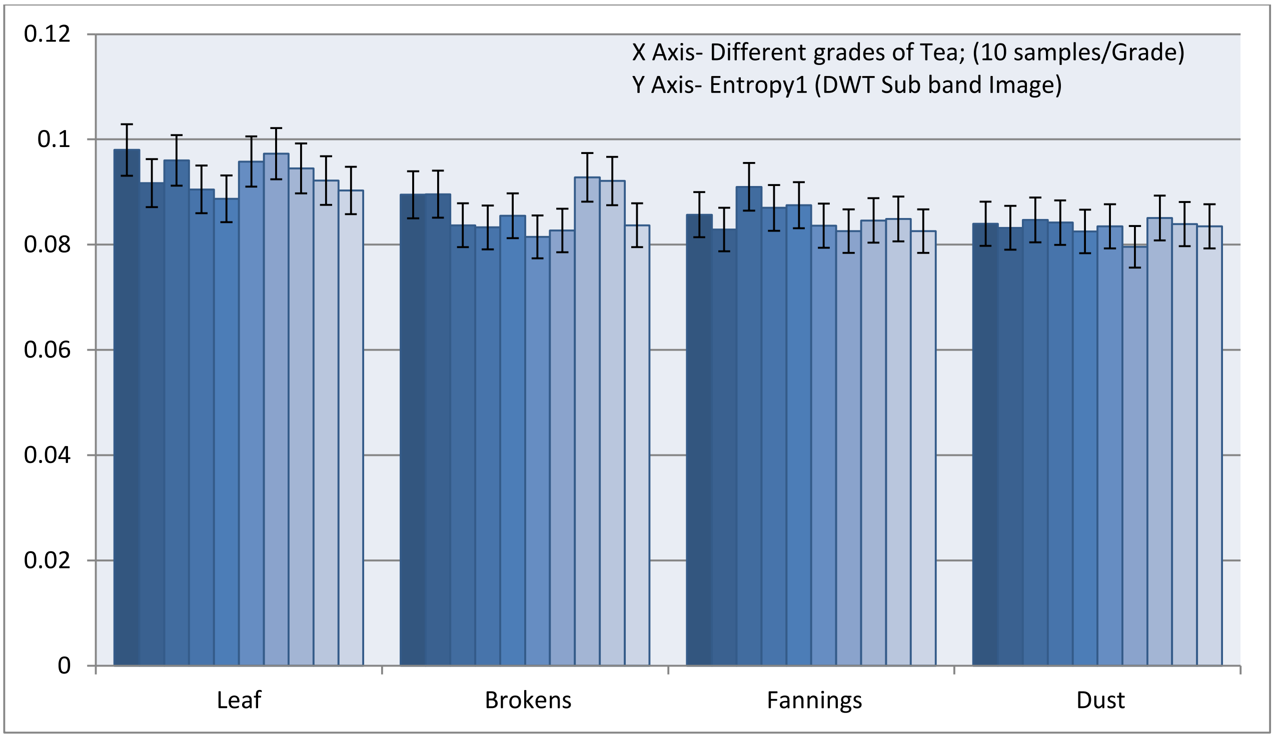

Figure 4.17: Entropy plots for various grades of tea (DWT Sub-Band Image; Level 1)

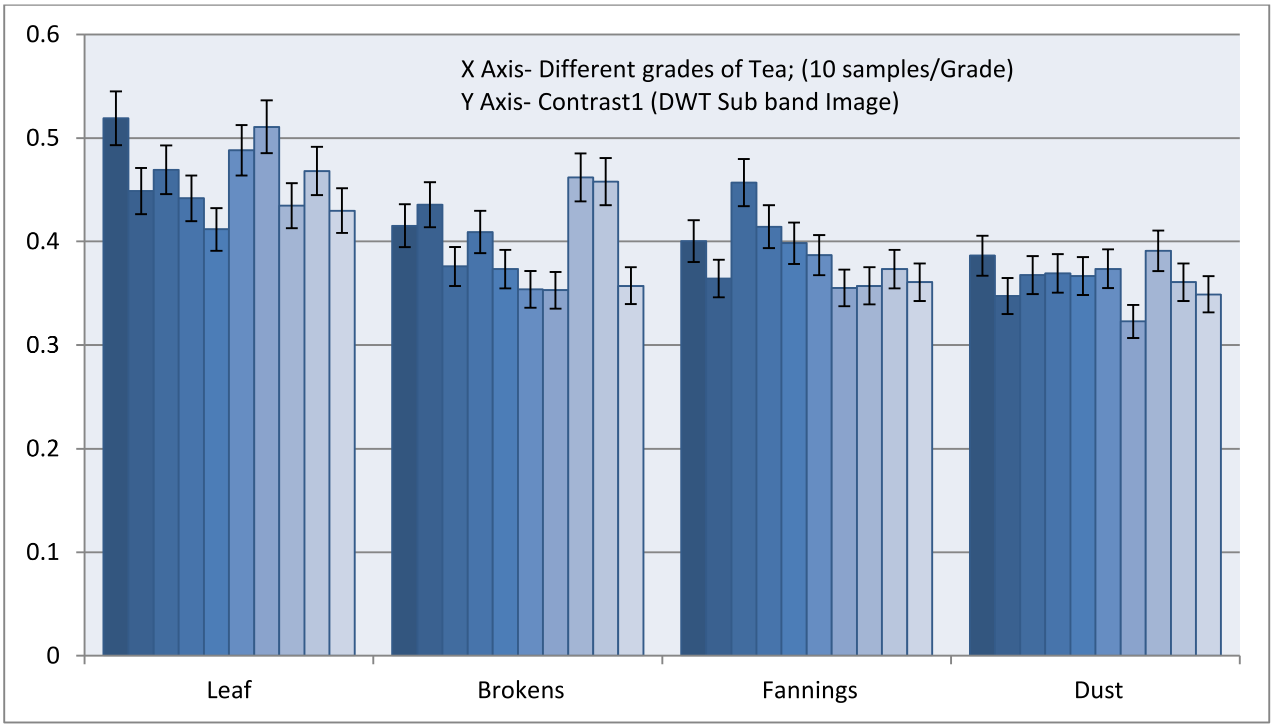

Figure 4.18: Contrast plots for various grades of tea (DWT Sub-Band Image; Level 1)

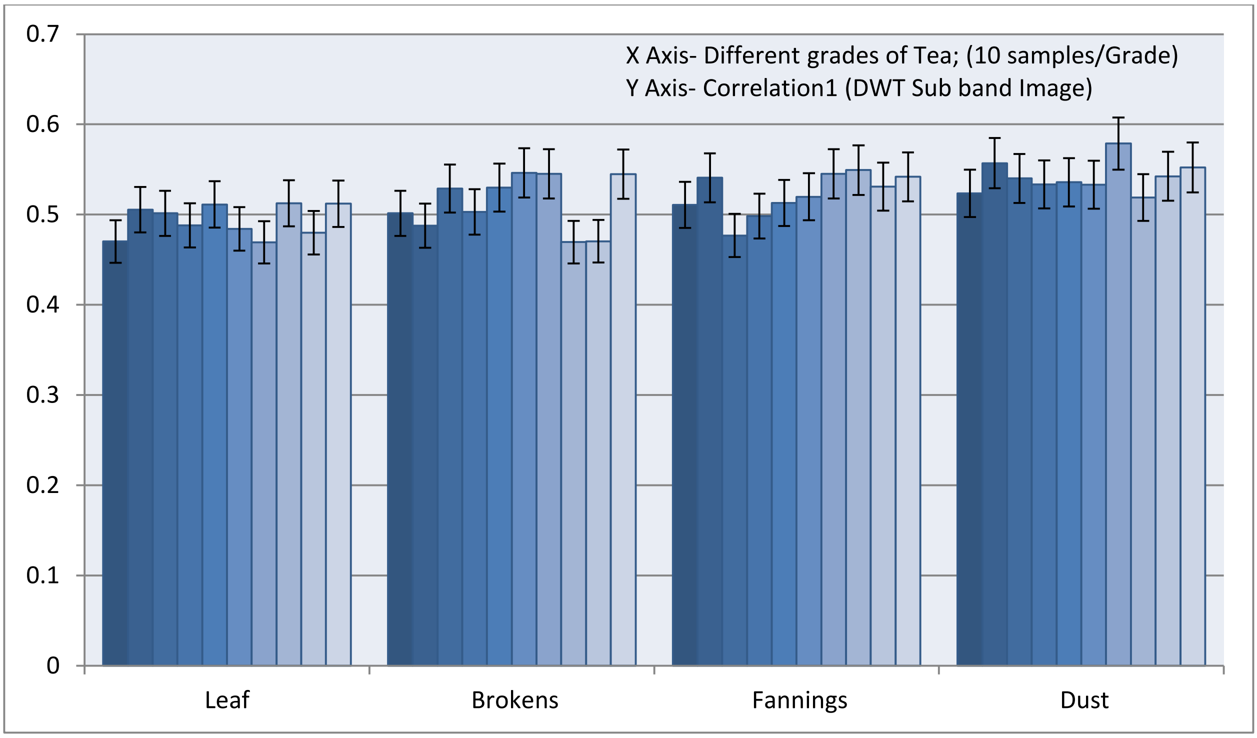

Figure 4.19: Correlation plots for various grades of tea (DWT Sub-Band Image; Level 1)

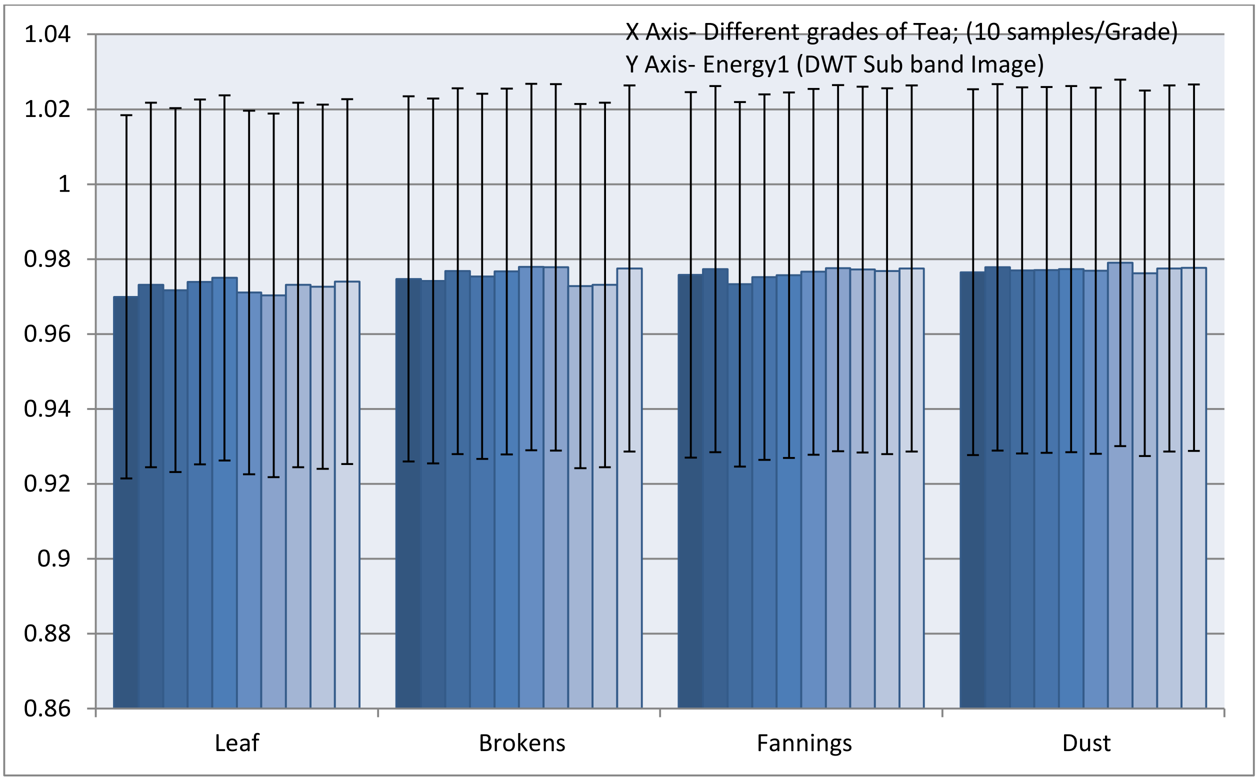

Figure 4.20: Energy plots for various grades of tea (DWT Sub-Band Image; Level 1)

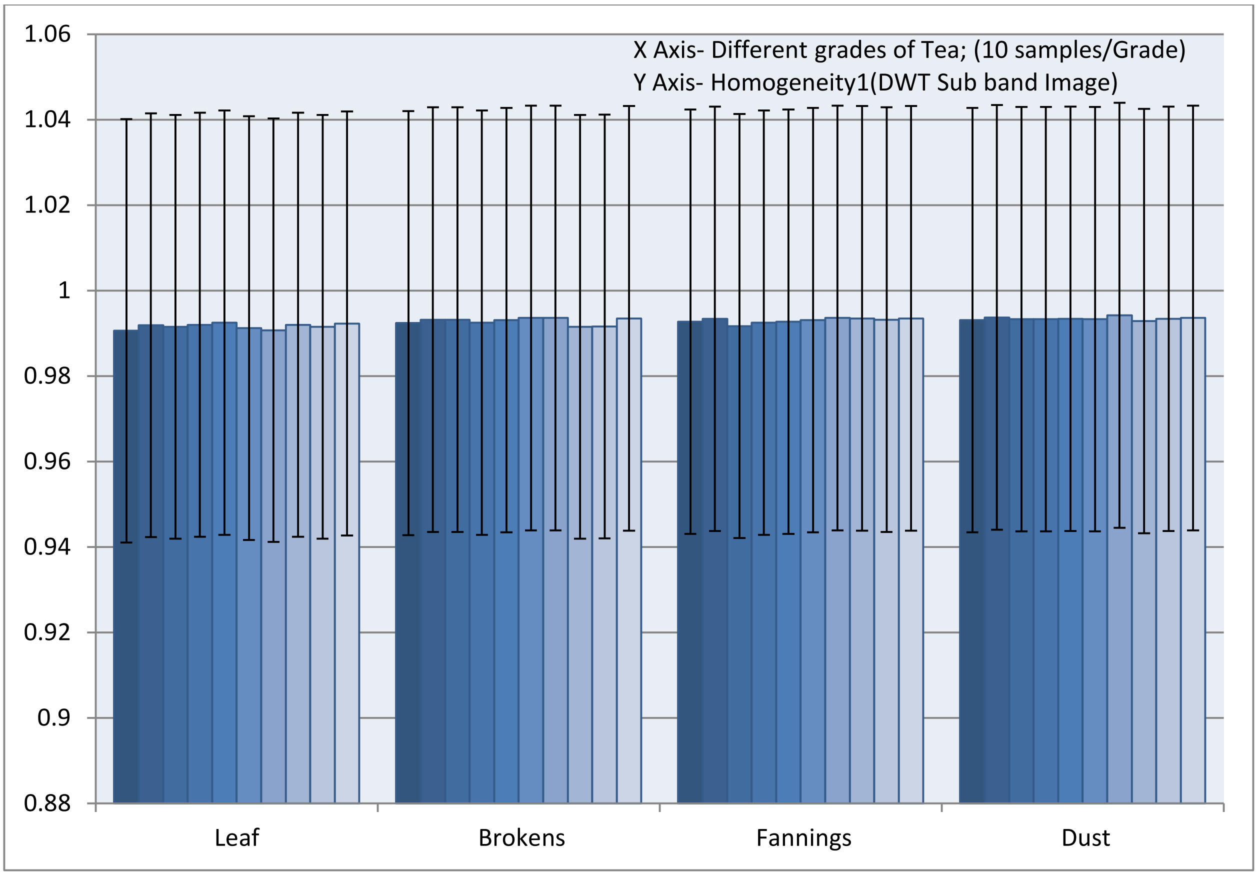

Figure 4.21: Homogeneity plots for various grades of tea (DWT Sub-Band Image; Level 1)

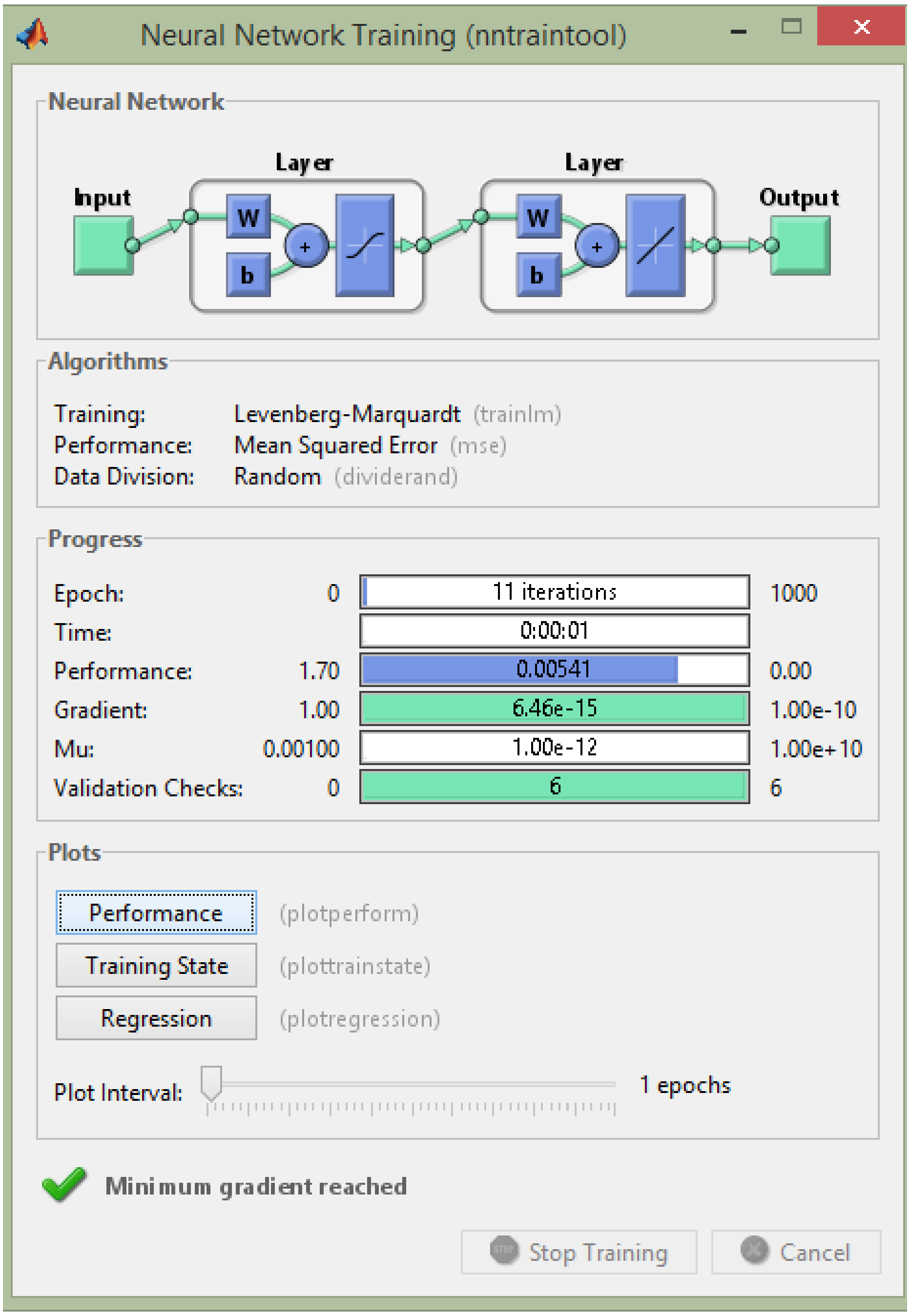

Figure 4.22: ANN classifier for Textural parameters (DWT Sub-Band Image; Level 1)

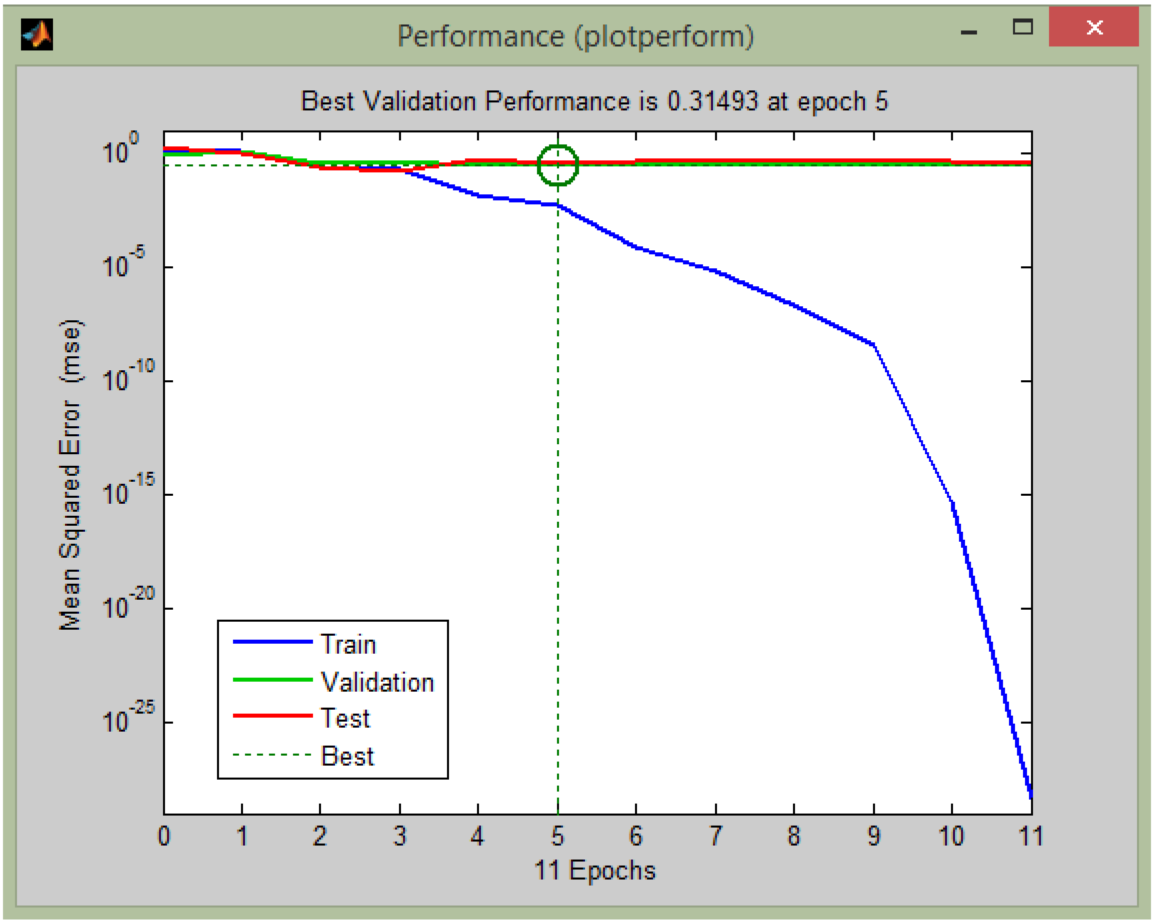

Figure 4.23: Performance plot of the ANN Classifier for Textural Parameters (DWT Sub-Band Image; Level 1)

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14/9/15 12:57 AM                    MATLAB Command Window

Total testing samples: 8

cm =

     0     0     0     0
     0     3     0     0
     0     0     1     0
     0     0     0     4

Percentage Correct classification   : 100.000000%
Percentage Incorrect classification : 0.000000%
```

Figure 4.24: Confusion Matrix for Textural Parameters (DWT Sub-Band Image; Level 1)

Further, regression plot (Fig 4.25) indicates perfect training with R=1, while the regression coefficient for validation and testing are 0.76812 and 0.81439, respectively. Ultimately, in the statistical analysis by ANOVA, all the textural features obtained from the level one sub-band images obtained by DWT, except entropy1, were found to have F* > F0.05 which indicates that all four grades can be significantly differentiated on the basis of each of these four textural parameters viz. contrast1, energy1, correlation1 and homogeneity1 (Table 4.7). The grading efficiency of textural method presented in this work is the highest compared to the other methods reported by the researchers (Borah, *et.al.*, 2007).

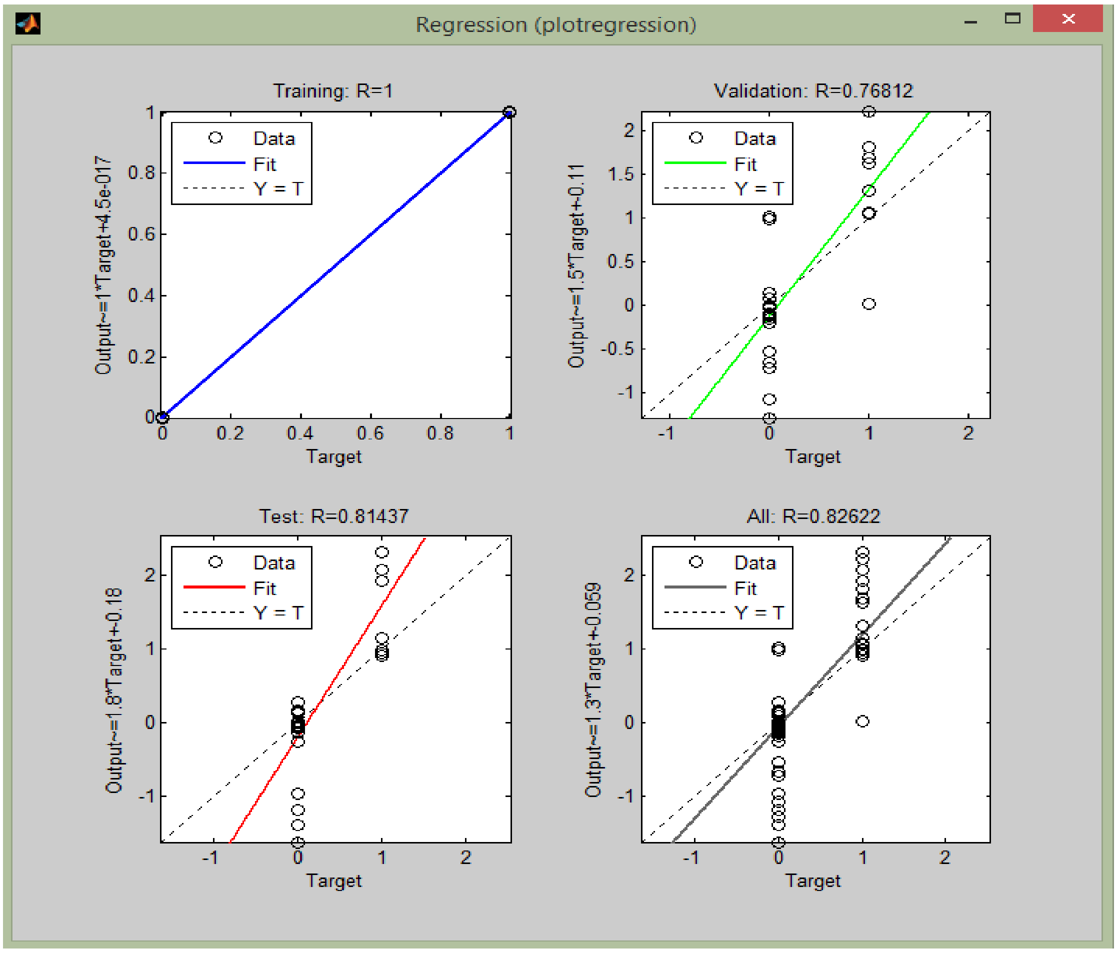

Figure 4.25: Regression plot of the ANN Classifier for Textural Parameters (DWT Sub-Band Image; Level 1)

Table 4.7: ANOVA results for Textural (DWT Sub-Band Image; Level 1) features

Feature	Observed Variance Ratio (F*)	Theoretical Variance Ratio ($F_{0.05}$)
Entropy1	0.002	2.84
Contrast1	111.15	2.84
Correlation1	85.74	2.84
Energy1	286.19	2.84
Homogeneity1	444.45	2.84

F*-Estimated (observed) variance ratio; $F_{0.05}$= theoretical value of at 5% level of significance

4.3 GRADING BASED ON COLOUR FEATURES

Tea liquor can be graded according to quality on the basis of its colour. The colour attributes corresponding to the average intensity of red, green and blue colours were computed from the images of tea liquor for four grades of tea (Table 4.8). For this purpose, a database of tea images comprising of five images for each grade was utilized. These images were captured under identical set of conditions and the samples for each of the ten images belonging to the same grade were drawn randomly from the same population. The fundamental reason of using more than one image for same grade was to ensure that any variations that may creep into the system due to various human factors may be reduced due to averaging effect. The graphical representations of colour features depicting standard error appear as in Figs. 4.26 - 4.28.

For classifying the data based on colour features, multilayer perceptron architecture has been used with two hidden layers having 14 and 13 neurons. The screen shot for ANN classifier is presented in Fig. 4.29 and the performance plot in Fig. 4.30. The best validation performance of 0.0026142 was obtained in the 11th epoch. The network returned 100% correct classification. **The confusion matrix in this case i**s 100% accurate (Fig. 4.31). **Performance plot** shows the mean square error dynamics for the datasets on logarithmic scale. Since the training MSE is showing a decreasing trend, so the validation and test MSE are the ones that have to be observed. The plot in this case shows a perfect training. Gradient value of 145e-16 indicates that the network has reached the bottom of local minimum of the goal function without any validation check.

Table 4.8: Colour features for various grades of Black Tea

Tea Grade	Red (on 0-255 scale)	Blue (on 0-255 scale)	Green (on 0-255 scale)
LEAF	252.5333	141.4844	19.4305
	252.5336	141.8668	19.4463
	252.5341	141.7301	19.4394
	252.5333	141.6534	19.4365
	252.5333	141.5708	19.4335
BROKENS	252.5317	95.9522	16.2653
	252.5294	95.7104	16.1996
	252.5307	95.8185	16.2233
	252.5312	95.867	16.237
	252.5315	95.9115	16.2514
FANNINGS	252.5068	90.8319	13.9596
	252.5248	91.4121	13.9697
	252.5194	91.1924	13.9649
	252.5157	91.0761	13.9631
	252.5116	90.956	13.9613
DUST	252.5309	70.2086	13.1434
	252.531	70.1143	13.1494
	252.531	70.1585	13.1468
	252.5309	70.1772	13.1453
	252.5309	70.1939	13.1444

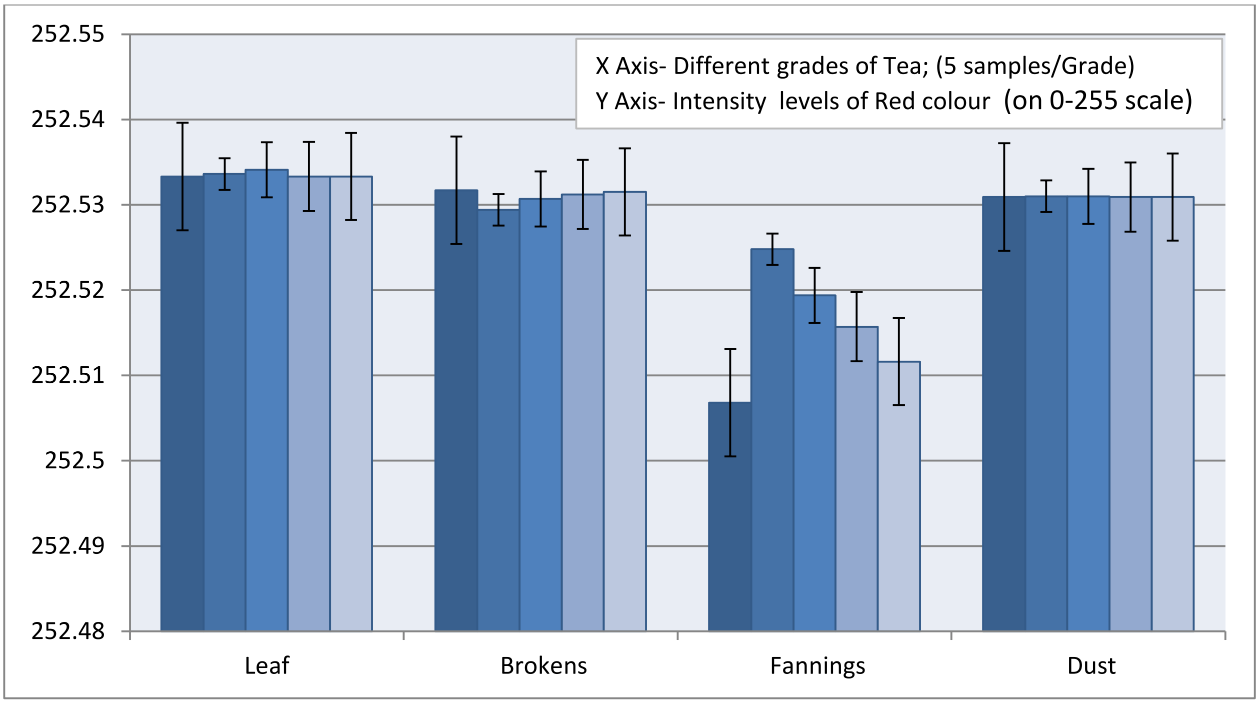

Figure 4.26: Red colour intensity plot for various grades of tea

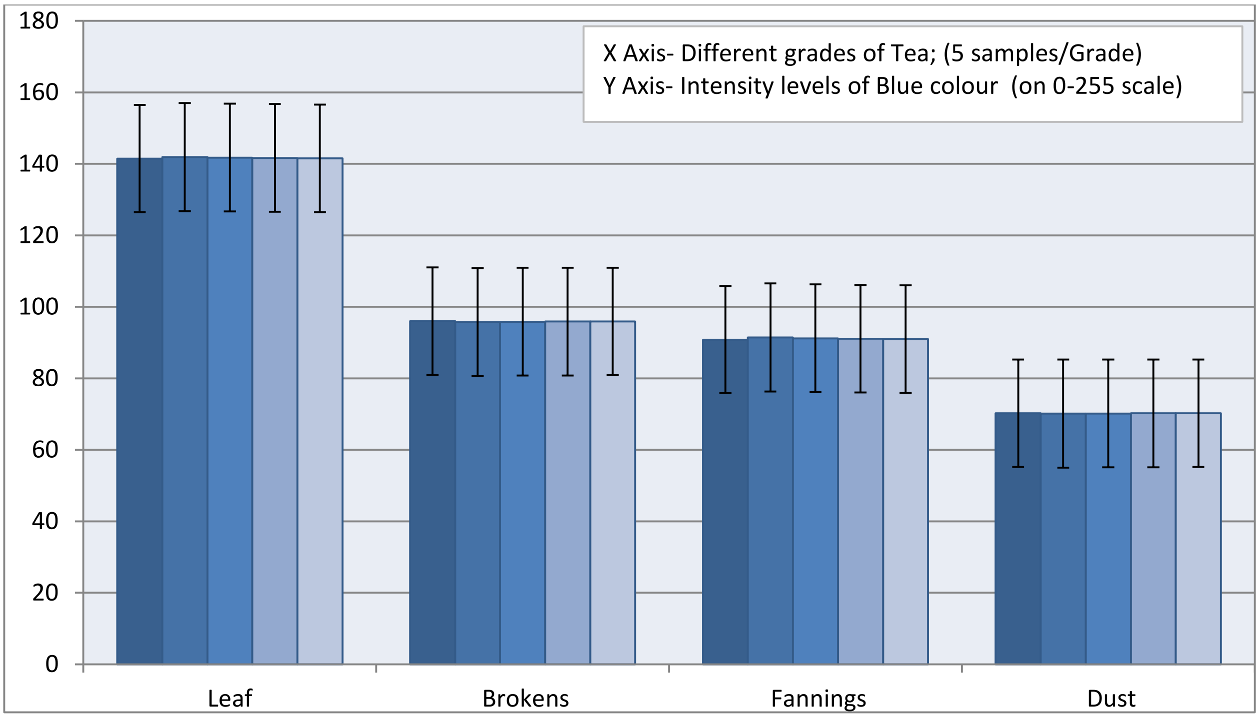

Figure 4.27: Green colour intensity plot for various grades of tea

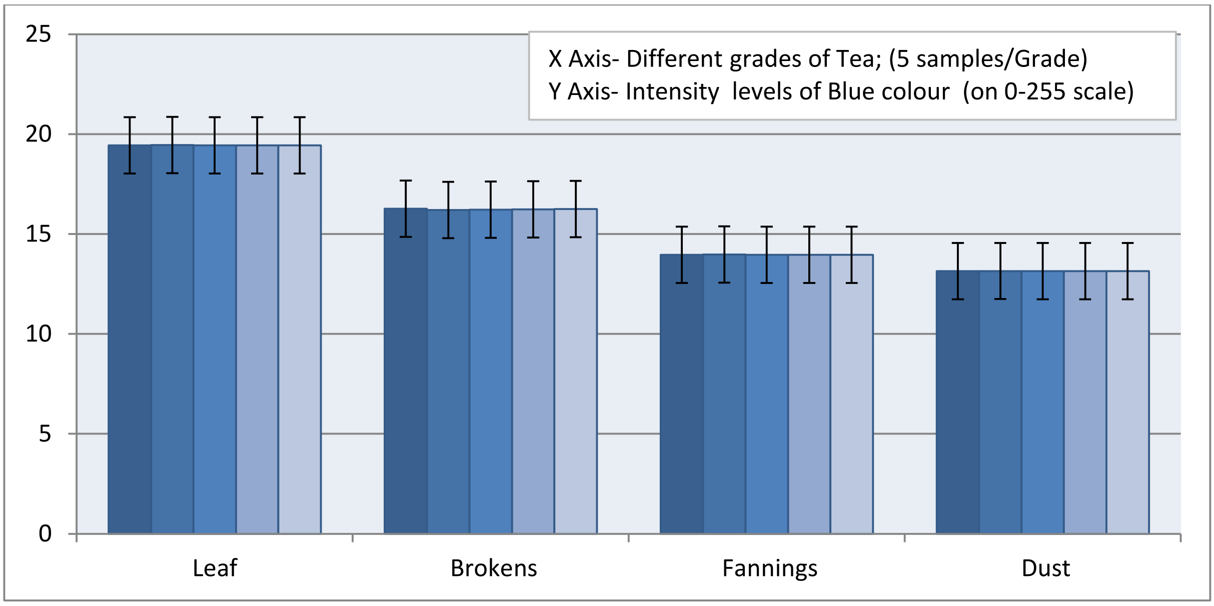

Figure 4.28: Blue colour intensity plot for various grades of tea

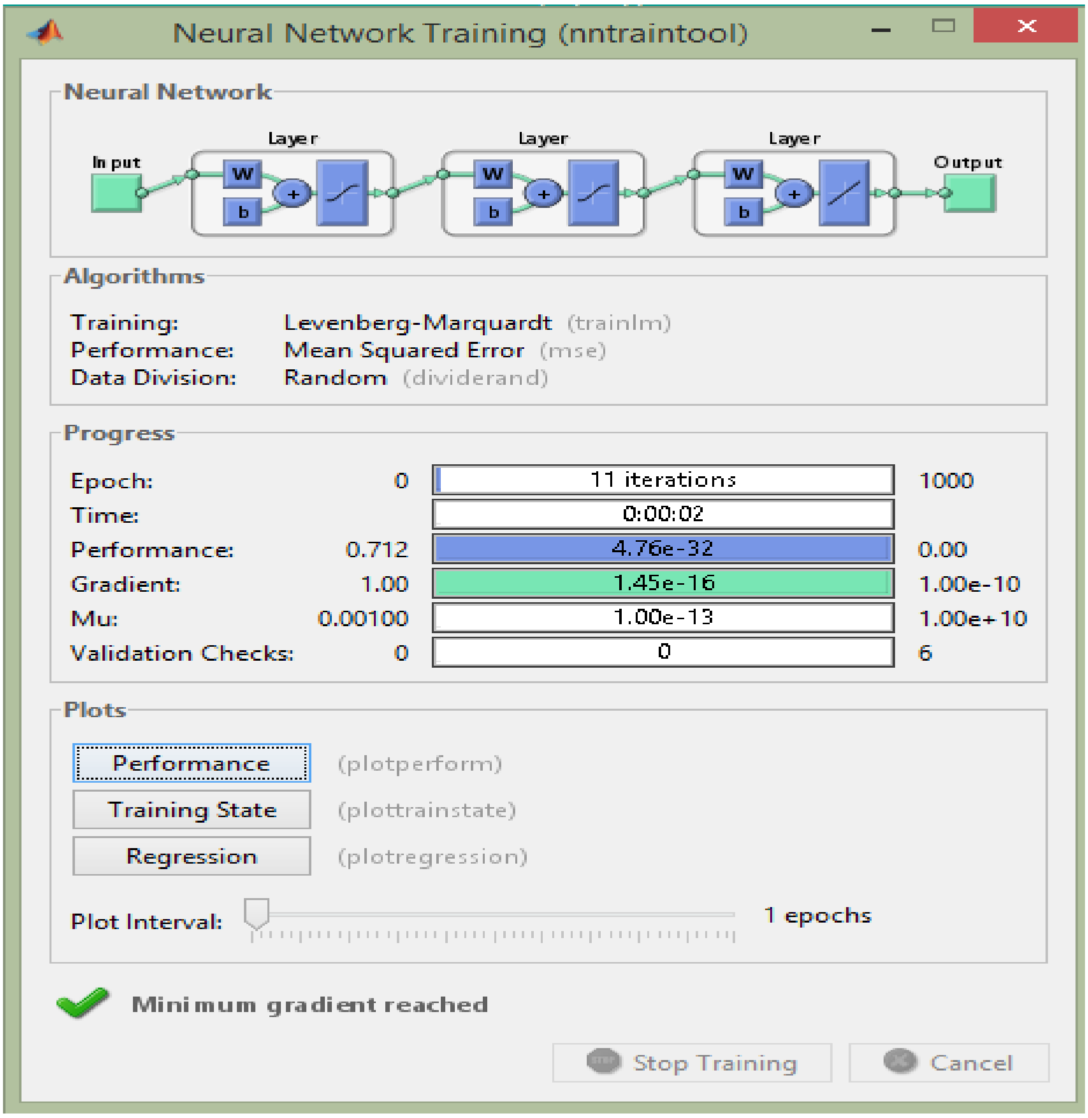

Figure 4.29: ANN classifier for Colour features

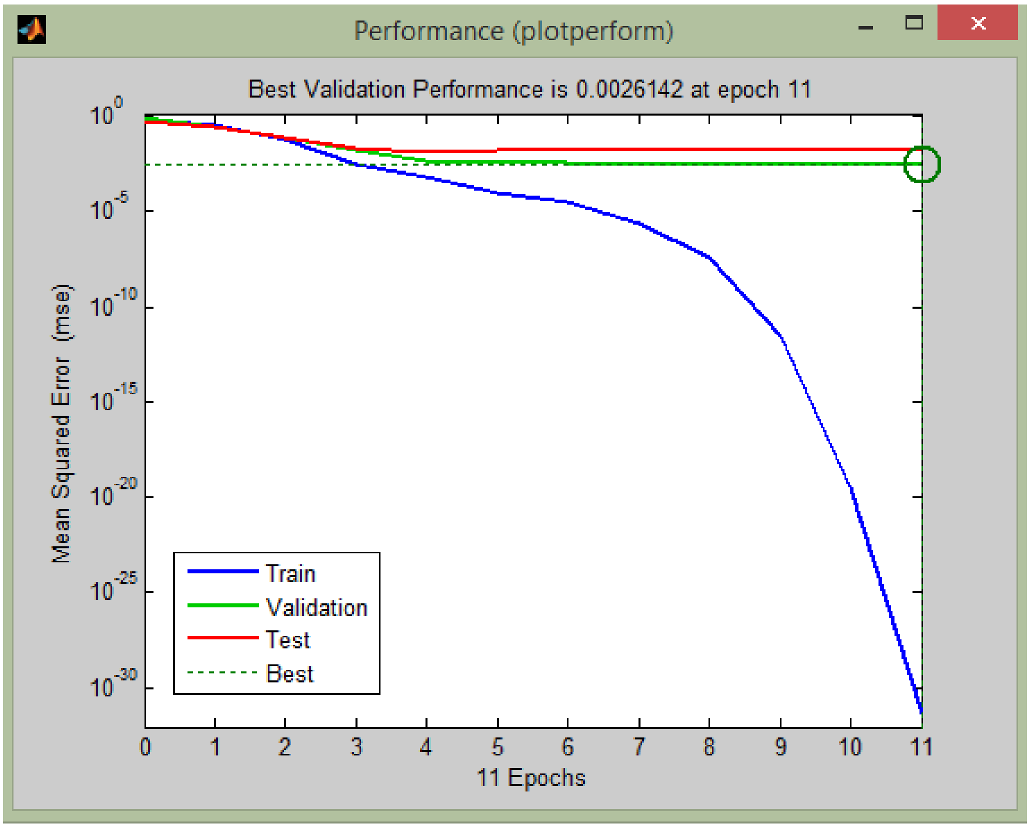

Figure 4.30: Performance plot of the ANN Classifier for Colour Parameters

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Total testing samples: 6

cm =

     1     0     0     0
     0     3     0     0
     0     0     0     0
     0     0     0     2

Percentage Correct classification   : 100.000000%
Percentage Incorrect classification : 0.000000%
```

Figure 4.31: Confusion Matrix for Colour Parameters

Further, regression plot (Fig 4.32) indicates perfect training with R=1. The four plots represent the training, validation, testing and overall data. The dotted line these plots correspond to ideal outcome where the outputs are equal to targets, while the bold lines symbolize the best-fit regression line. For the color feature set, the validation and test results also show regression coefficient of 0.99332 and 0.95921, respectively.

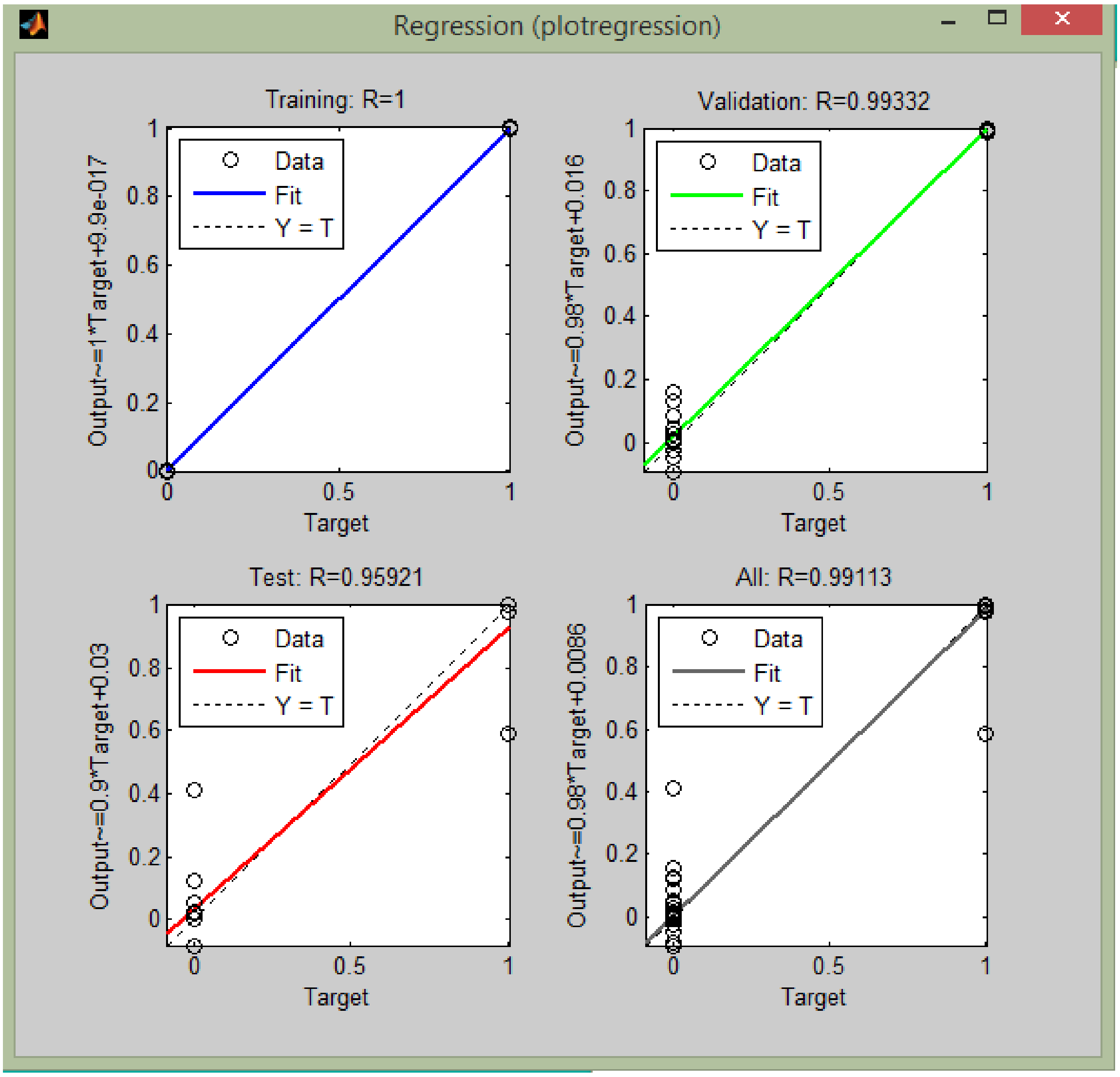

Figure 4.32: Regression plot of the ANN Classifier for Colour Parameters

In the end, statistical analysis is carried out by one-way analysis of variance (ANOVA) in which all the colour features have $F^* > F_{0.05}$ which means that the different grades can be considerably distinguished on account of each of the colour features (Table 4.9). The red colour had almost similar range for all grades, green colour proved to be the best one out of the all for discriminating amongst different grades closely followed by the blue. The grading efficiency achieved on the basis of colour was 100%, which endorses the suitability of proposed scheme for grading of tea.

Table 4.9: ANOVA results for Colour features

Feature	Observed Variance Ratio (F*)	Theoretical Variance Ratio ($F_{0.05}$)
Red	121.45	2.84
Green	317941.13	2.84
Blue	4545.43	2.84

F*-Estimated (observed) variance ratio; $F_{0.05}$= theoretical value of at 5% level of significance

4.4 GRADING BASED ON MOISTURE

Thermogravimetric analysis (TGA) was done for estimation of moisture for all four grades of tea. The moisture content for the four grades *viz*. leaf, brokens, fannings and dust are tabulated in the Table 4.10. TGA is a well known technique used for measurement of the changes in sample mass when heated. The readings given by the device are in the form of percent mass remaining for the sample when heated to 100°C as at this temperature, the moisture completely evaporates from the sample. Subtracting this value from 100, the moisture content in percentage is obtained.

Table 4.10: Moisture content by weight (in %) for various grades of tea

Grade	% Mass remaining at 100°C	Moisture Content
Leaf	96.136	3.864
Broken	96.708	3.292
Fanning	96.737	3.263
Dust	96.829	3.171

It can be observed that the tea granules having larger size (Leaf) has more moisture content compared to the granules having smaller size (Dust). In other words, the moisture content increases when we move from lower to higher grade or smaller sized granules to larger sized granules. This is due to the fact that the larger granules have more capacity to retain moisture due to their larger volume and when all these grades, prior to separation, are heated uniformly in the drier for removal of excess moisture, the smaller granules shed moisture relatively more than the larger granules. Though the TG based method used here for estimation of moisture in various has been used extensively for estimation of moisture content in various substances, its suitability was successfully tested for tea. Though moisture estimation has been done with consideration to the shelf life of the tea, but, moisture as a grading parameter of tea has been another noteworthy finding of this work.

4.5 GRADING BASED ON DENSITY

The bulk density of tea granules has been observed as a useful parameter in discriminating amongst tea grades. As the tea granules for different grades of black tea differ in shape and size and they have a different packing density. The bulk density of tea granules was estimated for tea granules of all four grades using two different ways i.e. the compacted and un-compacted. Both types of measurements have been tabulated in Table 4.11. It can be observed that with smaller grains of tea, more compactness can be obtained as with the smaller granules, the interparticulate void volume is considerably reduced and thus a more dense packing can be achieved. Due to this, the 'Dust' grade density is considerably high compared to 'Leaf' which has the least density compared to all the grades.

Table 4.11: Density of various grades of tea

Grade	Un-Compacted Density (g/cm^3)	Compacted Density (g/cm^3)
Leaf	0.360	0.390
Brokens	0.370	0.400
Fannings	0.420	0.470
Dust	0.510	0.620

From Table 4.11, it is evident that density increases as we move from larger granules to smaller sized granules. Moreover, the compacted density is always observed to be higher than the un-compacted density for the same grade. This is so because when the sample is tapped, the shock produced due to the tapping forces the loosely packed granules to occupy the interparticulate void volume, thus leading to a much more compact packing. It is obvious from the results that the variation in densities of various grades is very significant and this parameter can serve as an important parameter in the discrimination of tea grades.

CHAPTER 5
CONCLUSION AND FUTURE SCOPE

5.1 CONCLUSION

In this work, the potential of machine vision for quality assessment of black tea has been explored. In this context, the significant parameters in tea grading at the post processing stage are identified and assessment of quality has been done on the basis of these parameters. In this thesis, quality assessment of black tea is carried out on the basis of morphological, textural and colour features in addition to moisture and density. While the first three have been addressed using machine vision technique, the moisture and density are estimated by direct measurement. The image data gathered by acquiring the images of graded tea samples has been analyzed and relevant features are extracted using various image processing techniques and finally classified using an artificial neural network. Image database was formed for estimation of each category of features i.e. morphological, textural and colour. While the imaging of tea granules for estimation of morphological and textural features was carried out by directly placing them in a specific manner in front of the camera, the imaging for colour features involved preparation of tea liquor using a prescribed procedure whose images were then captured for extraction of colour features. Thus, while the former set of features were extracted in a purely non-destructive manner, the latter ones involved destruction of tea sample during the course of experiment. In this research work, a machine vision based method has been planned and implemented. The salient features of this method are its objective nature, independence from human variability and biases, which were the key shortcomings of the conventionally followed human sensory panel that has been in use in tea quality assessment till now.

During this work, different grades of tea were successfully discriminated on the account of certain morphological attributes like area, perimeter and aspect ratio. These features were estimated for the database comprising of images of four grades of tea, namely, leaf, brokens, fanning and dust. The results were compared with the standard graded samples obtained from tea industry. Finally, ANN is used for classification of extracted features with an accuracy of 100%. Results show good correlation of the proposed method with the standard samples duly evaluated by human experts. Statistical analysis by use of ANOVA (Analysis of Variance) highlighted area and perimeter as key attributes for discrimination between various grades on the basis of morphological features.

Further, the possibilities of discriminating various grades of tea granules on the basis of their texture were explored. In this thesis, a technique to discriminate between four different grades of made black tea using textural features based on grey tone spatial dependencies has been presented. This has been carried out keeping in view the fact that the different granule sizes offer a variation in textures when viewed. The statistical features, namely energy, entropy, contrast, correlation and homogeneity are estimated for the database of images of diverse grades. When these features are classified using MLP having one hidden layer, an accuracy of 87.5% was achieved. Further, these images were decomposed into sub-band images by DWT and the same features were computed from the sub-band image. When the same features were estimated for the sub-band images, the MLP returned an improved accuracy of 100%.

In the next section, colour estimation was carried out for discriminating the different grades on the basis of colour of the brewed tea liquor. The RGB model has been used in this work for estimating the average red, green and blue components in the images. Grade assignment was done on the basis of colour features extracted and 100% accuracy was observed when the extracted colour features were classified using MLP having two hidden layers. For statistical validation of the extracted features, ANOVA has been employed, which further elaborated the features that contributed in a more pronounced manner for the discrimination of tea grades. ANOVA gave the extent of variance contributed by a particular feature towards the total variance.

Another key parameter that determines the shelf life and storage quality of black tea is moisture. It was evaluated for different grades of tea. It has been established that the moisture retention is more in the grades having larger granules than the grades having smaller granule sizes. This is, probably, due to the fact that the larger granules retain relatively more moisture owing to their larger volume and when, prior to separation, all grades are subjected to uniform heating in drier for removal of excess moisture, the smaller granules shed more moisture compared to the larger granules.

Density is another parameter that assumes importance in context with grading of black tea. Compacted as well as un-compacted density has been estimated for different tea grades and it has been observed that the density enjoys an inverse relation with the granule size. As the granule size decreases, the density, both compacted and un-compacted, increases. Further the compacted density is always found to be more than the un-compacted density as due to tapping the interparticulate void volume is remarkably reduced, thus leading to more compact packing.

It is worth mentioning here that the procedures carried out in the present work for quality assessment are objective in nature and, except the colour analysis, are predominantly non-invasive in nature. Thus, these procedures involved almost no wastage of sample and can be useful for online grading and monitoring. If a system is developed using the proposed concept, it would be compact and portable. Moreover, it is expected that such a system, if developed, shall be very useful and beneficial for tea industry for preliminary evaluation of tea grading prior to wet chemical analysis.

5.2 FUTURE SCOPE

The work carried out in this thesis has an immense potential for extension. The following key points may be considered for extension of this work.

- The present work focuses on morphological, textural and colour feature along with moisture and density. If additional parameters such as aroma and taste are considered in addition to the physical features considered in this work, it may yield better results.
- Since texture is highly dependent on direction of illumination, an effort towards determination of optimal direction as well as intensity of illumination for best textural feature evaluation can greatly improvise the results (Sarkar, 1991)
- Although, MLP has given satisfactory results, it’s recommended that other classifiers may also be explored for such problems.

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