# Data Generation and Fruit Grading Using Different Classifiers

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***Abstract:*** **Grading of fruits is the post harvesting step involving the labeling of fruits into their respective categories using external (color, size, shape etc) and internal features(aroma, taste, pH etc). This could be done manually which is tiresome, inconsistent and time consuming task and therefore computer vision based fruit grading comes into play which makes the whole grading process consistent, labor saving and fast as well. In past years, researchers had introduced many non destructive image processing technique to grade the food products, ensuring quality of food products. This paper presents algorithm of classifying guava fruit into categories using Local Tetra patterns.Features extracted are classified using SVM, K-NN, Trees, ANNs. Results generated by different classifiers are analyzed using accuracy and error rate. Linear layer neural network gave the highest results amongst all the classifiers.**

**Keywords – Computer Vision, Fruit Grading, Guava, Local Tetra patterns, Classification**

## I. INTRODUCTION

Agriculture is the ruling occupation in India. Directly or indirectly, two-third of population is dependent on agriculture. It is not just a source of live hood but a way of life. India, it is the integral part of economic development and hence provides highest contribution to national income. Thus, it becomes essential to lift the impact factor of agriculture development.

India is a front runner in many fruits and vegetables. It ranks second in fruit and vegetable production after china. As per the national horticulture database published by National Horticulture Board during 2014-15, India produced 86.602 million metric tons of vegetables. The area under cultivation of fruits stood at 6.110 million hectares while vegetables were cultivated at 9.542 million hectares.

Thus it becomes essential to boost the production and productivity of vegetables and fruits in the country. Along with increasing their productivity, it is equally essential to label the quality of fruits and vegetables before dealing out. Labeling goods are done manually by human by observing the external feature like color, shape, size etc. Since manual inspection is time consuming, tiresome and inconsistent as well, since it is human nature to become inattentive after a period of time. Thus automatic grading system of goods basis on various factors give accurate, consistent and efficient outputs, resulting in saving time and assisting the economic development.

For determining the quality of fruits, external and internal quality features are taken into consideration. Some of internal quality factors are sweetness, aroma, taste, sourness, nutritive value like minerals, vitamins etc and external quality factors are color, size, shape, texture, surface defects.

In this research, we proposed algorithm for classification of guava fruit into four categories namely unripe, ripe, overripe and defected. Statistical, texture and geometric are extracted followed by using various classifiers. The paper of organization is as follows section 2 briefly explain the related work, section 3 deals with the materials and methods, section 4 describes the proposed method. In section 5 results are discussed and section 6 is conclusion and future scope.

## II. RELATED WORK

The design requirements for grading different fruits vary from fruit to fruit building a dedicated system focused on particular product or fruit has been the aim of many researchers. Kondo 2003 [1], Gay and Berruto 2002 [2] built common fruit grading and classification system, but dedicated system available sort particular type of fruit only. Researchers built dedicated system to sort apples (Unay and Gosselin [3]; Mehl et.al,[4]; Li andHeinemann [5] ), banana (D. Surya Prabha et.al, [6]; Wei Ji et.al, [7]; Meng-Han Hu et.al, [8]; Alireza Sanacifier et.al, [9] ), tomato (Laykin et.al, [10]; Polder et.al,[11]), citrus fruits (Aguilera et.al, [12]; Regunathan and Suk Lee [13]; Calpe et.al,[14]), date (Yousef Al Ohali [15]), pepper berries ( Abdesselam and Abdullah [16]).

Performance of different sorting and grading system depends upon the quality factors taken into consideration. Quality factors used by farmers areexternal and internal factors as mentioned earlier in introduction section. For grading of fruits, non destructive and standardize technique is required hence computer vision based fruit grading comes into play. The captured image of fruit is converting into digital image. Various image processing techniques are applied on digital image to extract features which are then used for classification as shown in Fig 1.

 

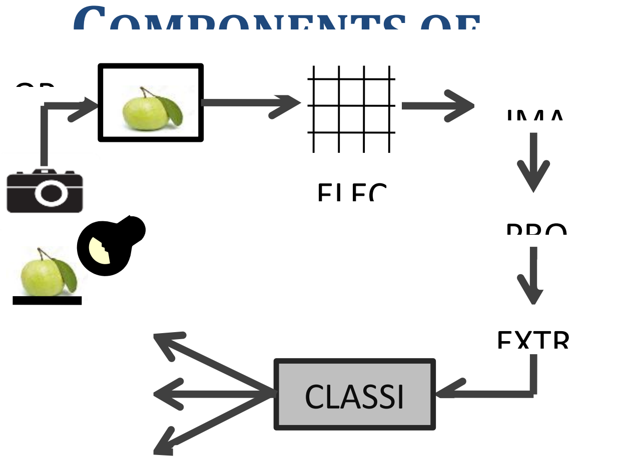


Fig 1 : Components of Computer Vision System

To automate the apple grading , Devrim Unay et.al,[17] extracted color,shape, size and texture based features from segmented multispectral images. Images are captured by high resolution black and white camera with different band pass filters followed by specific segmentation of defective part and then categorizing fruit. From all the features extracted, total of 67 features are selected since it is infeasible and irrelevant to use all features since it degrades the performance of the system. Various classifiers used for classifying fruit into respective categories are Nearest Neighbor classifier (K-NN), Support Vector Machine (SVM), C4.5, Linear Discriminant Classifier. From all above mentioned for two-category grading, SVM performed well with 86.5% recognition rate when all features extracted taken into consideration, while with features selection SVM gave 93.5% recognition rate. For grading fruits into multicategory two approaches were used (i) Direct approach where fuzzy K-NN achieved highest of 83.5% recognition rate and (ii) Cascading approach consisting of SVM(85.6%) followed by fuzzy K-NN. From direct approach and cascading approach, direct approach is preferred with limited computatational resources and cascading approach is better choice if significant accuracy is required.

Suresha M et.al,[18] segmented apples using threshold from HSV images , then average green and red components are used in classifying apples using SVM classifier achieving 100% accuracy. M.Khojastehnazhand developed lemom grading system consisting of two CCD cameras, lighting system , two capture cards, computer and mechanical parts. Color evaluated from HSI color and volume calculated by dividing the image into number of different sectors. Values of color and volumes are then compared with saved values in database.

J. Blasco et.al, [19] detected pee defects in citrus by using region selecting, growing and merging algorithm. It involves selecting the seeds from appropriate region of interest and that grows iteratively by addition of neighboring pixels satisfying the criterion. After region growing, images is segmented into many regions. Among many segmented area, largest area is determined which is assumed to be sound skin of fruit thus failing the approach if area of defected skin comes out the largest area. An expert measured the performance of proposed system and accuracy of detecting defects was 94%.

Megha P. Arakeri et.al, [20] developed computer vision based tomato grading system consisting of fruit handling and image processing module. Median filter applied on captured images to eliminate the noise and reflections. Resulting images was segmented using Otsu's method [21] and features extracted from individual channel of RGB image are mean , standard deviation , skewness (statistical) and contrast, homogeneity, energy, correlation (texture features) from GLCM matrix. For classifying tomato as ripe or unripe , mean color values of each component from RGB image is extracted based on some threshold value. For optimal feature selection, Sequential Forward Selection (SFS) is applied. Classification using Multilayer Neural Network obtained accuracy of 100% for defective/non defective and 96.47% for ripe/unripe tomatoes.

Ruchita R.Mhaski et.al, [22] introduced tomato grading system using Rasberry Pi ( processor manages motors and Pi camera) for image analysis. From images captured, redness, yellowness and greenness from HSV images of tomato and maximum of three defines the ripeness stage of tomato. Using pixel count of each color , shape and size are estimated by dividing image into contours, finding biggest of all and labeling it as the fruit size. K-mean clustering detect the defects in tomato images.

D.Surya Prabha et.al, [6] determined the banana fruit maturity by use of color intensity obtained from the banana histogram. Banana region is segmented from the background using a threshold value. Maturity stage of banana is determined using statistical moments from histogram , moment about the mean is calculated. Variance determine the smoothness texture. Number of pixels in banana region calculate the area, number of pixels in boundary region assess the perimeter. Pixels are converted into a measurement unit of centimeter. The proposed method measure maturity of banana finger but under field condition , banana exist as bunches and this was shortcoming . Accuracy of 99.1% for color value and 85% for size value determination was obtained.

Wei Ji et.al,[7] measured the ripeness level of banana with the use of grade color chart of banana given by ASDA. The RGB image of banana was converted to CIE XYZ images followed by separating color into four clusters. The colorfulness(C), lightness (L) and Hue (H) for every pixel were calculated and then values are averaged for further use. For colored areas, image clustering method calculate Euclidean distance with four user defined color centers. Distance obtained if lies within specified range, it is categorize to that color centre. In this research, comparison between spectrophotometry and digital imaging was made proving digital imaging showed improved results and is more flexible and consistent.

 

Meng-Han Hu et.al, [8] used computer vision based size determination technique for banana. The five point method along with Euclidean distance was used to estimate the indicators of banana size i.e. length arc height and ventral straight length. Comparison of manual, semi automatic and automatic size determination was made , showing automatic method works better.

Alireza Sanaeifer et.al, [9] predicted banana quality indices using color features. Various banana quality indices are pH, firmness, total soluable solids, titratable acidity. For extracting color information, background was removed from image and the resulted image was converted into HSV and l*a*b color spaces. From banana surfaces , red, blue, green, saturation, hue, intensity, lightness and a*, b* components was determined and saved for further analysis. Correlation between color information and quality indices are analysed like greener the banana lower the TSS ( a*), yellow the banana higher the acidity (b*), more ripe banana less is the firmness (Hue value). Capability of support vector regression (SVR) and Artifical neural network (ANN) was evaluated and SVR showed better results.

To automate mango ripeness evaluation using image processing, Ramya M et.al, [23] cropped the mango area and segmented using Otsu's method with threshold value. Dividing the segmented image into three region namely equator, apex and stalk region and calculate the average of each color channel of RGB image. K-NN algorithm calculate the Euclidean distance using stored value of mangoes with those of values of unknown mangoes and thus classifies mangoes using the nearest distance with accuracy of 93%.

Yousef Al Ohali [15] degined and implemented grading system for data fruit and fruit is categorize as small, medium and big. Using variance and average area relationship, shape is estimated from edge tracking operator. Date with high intensity is considered as better quality and thus intensity is measured by area covered by edges divided by total fruit area. Defects in date fruit i.e bird flicks are estimated by use of brightness value of pixel and bruises are determined from the shape. After various features extracted . fruit is classified using back propagation neural network and obtained 80% accuracy.

Malay Kishore Dutta et.al,[24] classified grapes, exposed to pesticide. Four fluorescent lamps and from CFL were used to illuminate the samples. Camera used for capturing samples is NIKON D7000. Proposed system classifies grapes into pesticide treated and untreated grapes. It involves segmentation of region of interest from bunches of grapes. 18 Features are extracted from wavelet transformated segmented ROI using haar filter. Features extracted are input to SVM classifier and accuracy obtained was 100%.

Hassan Sardar [25] estimated guava fruit quality by non destructive technique. This research involves color as primary feature and day light, colorization, shape, size, softness, hardness, day temperature contribute to quality analysis as well. For classifying guava into different categories, updated Hassu algorithm was used, for detailed description refer [25].

The range of values obtained from algorithm are assigned to each category, thus the value generated by a input was matched to existing specified range and category was assigned appropriately.

In literature, for texture feature extraction, Local Tetra Pattern (LTrps) by Subrahmanyam Murala [26]. had not been used, thus this motivated us to use LTrPs and analyze the results. Also,due to unavailability of public database, guava database had been created.

**MATERIALS AND METHODS**

The categorization of guava fruit is based upon color, shape, size, texture into four categories (unripe, ripe, overripe and defected) primarily involves collecting samples and image aquistion. Sample images were captured through camera and Matlab R2015a was for manipulation of images. Modules involved in the estimation of category of guava fruit are discussed below

Sample collection and Image Acquisition

Samples of guava are collected from local market; the category of each sample is decided from survey of 20 people. Every person after looking at the guava image label it as ripe, unripe, overripe and defected, then maximum votes a sample gets for particular label is named as same. Images are captured by a NIKON S2600 camera and its specification are detailed below

- 14.0 mega pixels
- Lens- 5x zoom
- Image sensor-1/2.3-in
- Interface- hi speed USB
- Type- CCD

Guava fruit were placed at white background to simplify the task of segmentation and camera was located at distance of 12-15 cm from guava and vertically at angle of $80^{\circ} - 90^{\circ}$ and manually oriented the side of fruit. Images are captured during day light and image size was set to 640*480 pixel, ISO Sensitive- 400 and format- JPG. Total of 113 images are collected successfully comprising of ripe, unripe, overripe and defected.

## III. PROPOSED ALLGORITHM

The proposed method uses image processing technique and various classifier to categorize the guava fruit into four respective categories namely ripe, unripe, overripe and defected. This involves segmenting the fruit image from background and extracting color, size, shape and texture features. Table 1 gives the brief information about the parameter used for various features ( detailed explanatiion of LTrPs is given in section 4.5).

Table 1: Parameters used for various features extraction

Various classifiers used for classification of guava fruit with proposed method are Support Vector Machine, Artificial

| Features extracted | Parameter used |
| --- | --- |

| | |
|---|---|
| *Color value extracton* | mean<br>median<br>variance<br>standard deviation |
| *Shape and size value extraction* | area<br>perimeter<br>roundness<br>equidistant<br>circularity<br>major axis<br>minor axis |
| *Texture features extraction* | Local tetra patterns (LTrPs) |

Table 1: Parameters used for various features extraction

Various classifiers used for classification of guava fruit with proposed method are Support Vector Machine, Artificial Neural Networks, K- Nearest Neighbors, Trees and Ensemble Classifiers. Fig 2 represents the flowchart of the proposed method.

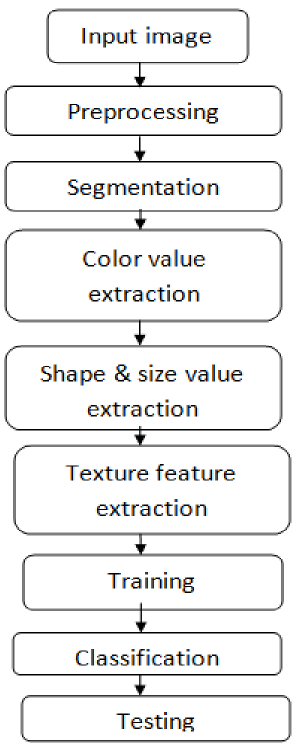


Fig 2 : flowchart of the proposed method

*4.1 Preprocessing* :- To eliminate the noise and reflection, median filter was applied to the input image.

*4.2 Segmentation*:- Convert the processed RGB image to gray scale image followed by conversion to binary image using threshold value, where binary image contain 1's in the fruit region and 0's in the background. Binary image obtained is multiplied with each color channel of original processed RGB image and then concatenated together to get the guava region named as segmented image.

*4.3 Color value extraction* :- Color of guava determine the ripeness level, thus is the primary feature. From segmented image, mean and median (for each color component), variance and standard deviation is calculated.

*4.4 Shape and size value extraction* :- From the binary image, *area* is counting number of pixels having value 1, perimeter counts number of pixels having value 1 at the edges of guava region.

$$\text{circularity} = \frac{perimter\text{^}2}{area} \quad (1)$$

$$Diameter = \frac{major\ axis + minor\ axis}{2} \quad (2)$$

$$Equidistant = \frac{4*area}{3.14} \quad (3)$$

$$Roundness = \frac{4*3.14*area}{perimtere\text{^}2} \quad (4)$$

Total 10 geomteric features are computed.

*4.5 Texture features* :- For computing texture features, Local Tetra Pattern proposed by Subrahmanyam Murala [26] encodes connection between a given pixel and its neighbors. The concept of local patterns namely local binary patterns (LBP)[27], local derivative patterns (LDP) [28] and local ternary patterns (LTP) [29] lead to defining of LTrPs. LBP, LDP and LTP uses two direction(positive and negative) for extracting the information where LTrPs uses four directions. Performance of LTrPs was compared to LBP, LDP and LTP and has significantly improved from previous local patterns . LTrPs uses gray scale image and traced the spatial structure with the use of the centre pixel's direction $R_c$. For calculating direction of centre pixel $R_c$ in image M, we need to determine $M_{0^\circ}$ and $M_{90^\circ}$.

$$\text{where} \quad M_{0^\circ}(R_c) = M(R_h) - M(R_c) \quad (5)$$

$$M_{90^\circ}(R_c) = M(R_v) - M(R_c) \quad (6)$$

$R_h$ and $R_v$ are vertical and horizontal neighbor of centre pixel $R_c$. Direction calculation of $R_c$ is as follows

$$M'_{dir}(R_c) = \begin{cases} 1, & M_{0^\circ}(R_c) \geq 0 \ \& \ M_{90^\circ}(R_c) \geq 0 \\ 2, & M_{0^\circ}(R_c) < 0 \ \& \ M_{90^\circ}(R_c) \geq 0 \\ 3, & M_{0^\circ}(R_c) < 0 \ \& \ M_{90^\circ}(R_c) < 0 \\ 4, & M_{0^\circ}(R_c) \geq 0 \ \& \ M_{90^\circ}(R_c) < 0 \end{cases} \quad (7)$$

For every pixel in image M, is converted to 1, 2, 3, 4 values. Now, , $\text{LTrPs}^2$ $(R_c)$ is calculated as

$$= \{ g_3(M'_{dir}(R_c), M'_{dir}(R_1)), g_3(M'_{dir}(R_c), M'_{dir}(R_2)), \ldots\ldots\ldots g_3(M'_{dir}(R_c), M'_{dir}(R_p))\} \Big|_{p=8} \quad (8)$$

where $g_3(M'_{dir}(R_c), M'_{dir}(R_p))$

$$= \begin{cases} 0, & M'_{dir}(R_c) = M'_{dir}(R_p) \\ M'_{dir}(R_p), & \text{else} \end{cases}$$

From equation R & M; for every pixel 8-bit tetra pattern is obtained and for every direction of centre pixel, we divided patterns into 4 parts, followed by conversion into three binary patterns for each part as shown

$$LTrP^2\big|_{direction=2,34} = \sum_{q=1}^{q} 2^{(q-1)} \times g_4(LTrP^2(R_c)\big|_{direction=2,34} \quad (9)$$

$$\text{where } g_4(LTrP^2(R_c)\big|_{direction=\phi} = \begin{cases} 1, & \text{if } LTrP^2(R_c) = \phi \\ 0, & \text{else} \end{cases}$$

Thus, for total of four directions 12 (4*3) binary patterns are obtained. For magnitude determination of every pixel, $13^{th}$ binary pattern (MP) is included as follows.

$$T_{M'_{(R_p)}} = \sqrt{(M'_{0^\circ}(R_p))^2 + (M'_{90^\circ}(R_p))^2} \quad (10)$$

$$\text{MP} = \sum_{q=1}^{q} 2^{(q-1)} \times f_1(T_{M'(R_p)} - T_{M'(R_c)}\big|_{q=8} \quad (11)$$

Total of 13 binary patterns for every pixel is generated; these 13 patterns are used to construct histogram. From combined histogram, feature vector of length $2^q$ is constructed. In this research, feature vector (FV) of known sample of unripe, ripe, overripe and defected guava fruit is constructed. From four saved FVs, every input image' FV is subtracted and result is summed up ( negative values are taken as positive). Thus for each input, we get four summed up values ( i.e. for unripe, ripe, overripe and defected category), these values are used for further analysis.

*4.6 Training and testing:* Data comprise of total 22 features extracted for each image. In this study, we have evaluated the performance of the proposed method on database having three different percentages of training and testing data as shown in table 2. Outputs on each data sets using different classifiers are analyzed in section 5.

| Set no. | Percentage of data used for training | Percentage of data used for testing |
|---|---|---|
| *1st set* | 60% | 40% |
| *2nd set* | 70% | 30% |
| *3rd set* | 85% | 15% |

Table 2 : percentage of data used for training and testing

*4.7 Classification* : All the features extracted are used for classification of guava fruit into four categories namely unripe, ripe, overripe and defected. List of classifiers are used for classification are Support vector Machine (SVM), K-NN classifier, Artifical neural networks, Decision trees.

## 5. RESULTS AND DISCUSSIONS

This section presents the results produced by different classifiers on dataset, comprising of different percentage of training and testing data. Accuracy and error rate of every classifier is evaluated and plotted as shown in figures.

**SVM** - It gave highest accuracy of 87.5% when linear kernel function is used and percentage of training and testing is 85% and 15% respectively. Fig 3 shows the accuracy obtained with different kernels functions namely Linear , Quadratic, Cubic, Fine Gaussian, Medium Gaussian and Coarse Gaussian kernel.

**K-NN** – Different options of nearest neighbors are used like fine, medium, coarse, cosine, cubic and weighted K-NN classifier and results are analyzedin terms of accuracy and error rate. From all the mentioned options, weighted K-NN performs better with accuracy of 81.3% on dataset when 85% of it is used for training. Fig 4 presents the accuracy.

**Decision tree classifier** – Simple, medium and complex trees are used and results are evaluated as shown in Fig 5 Simple trees performed better then medium and complex trees.

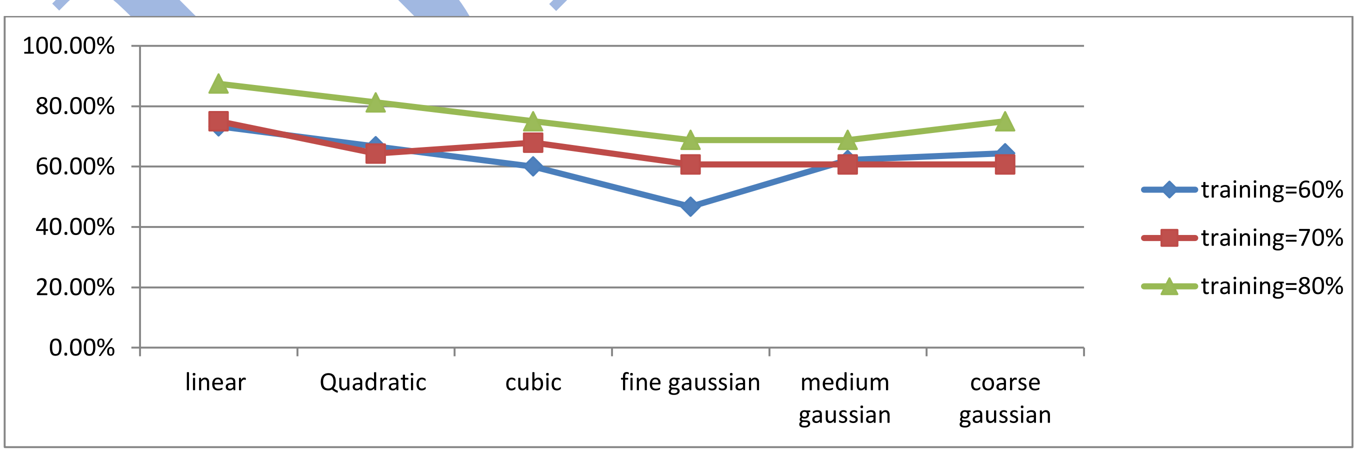


Fig 3: Accuracy of SVM classifier with different kernels

 

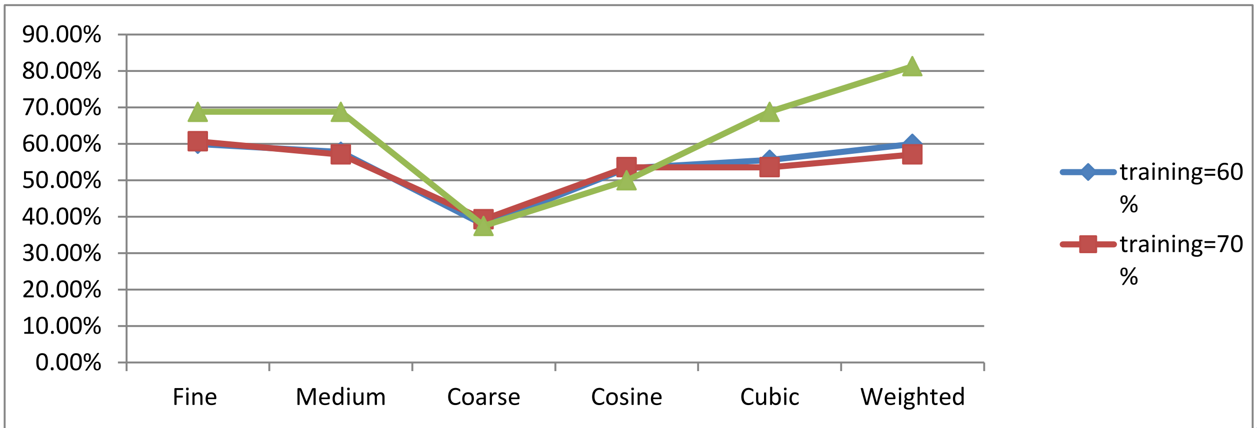


Fig 4 : Accuracy of different K-NN classifiers

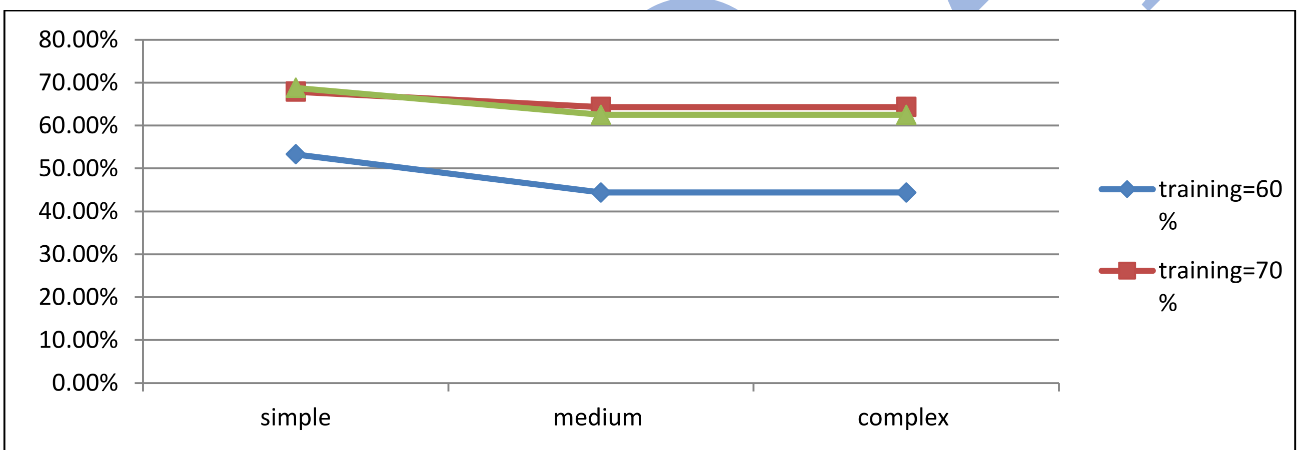


Fig 5 : Accuracy of different trees classifiers

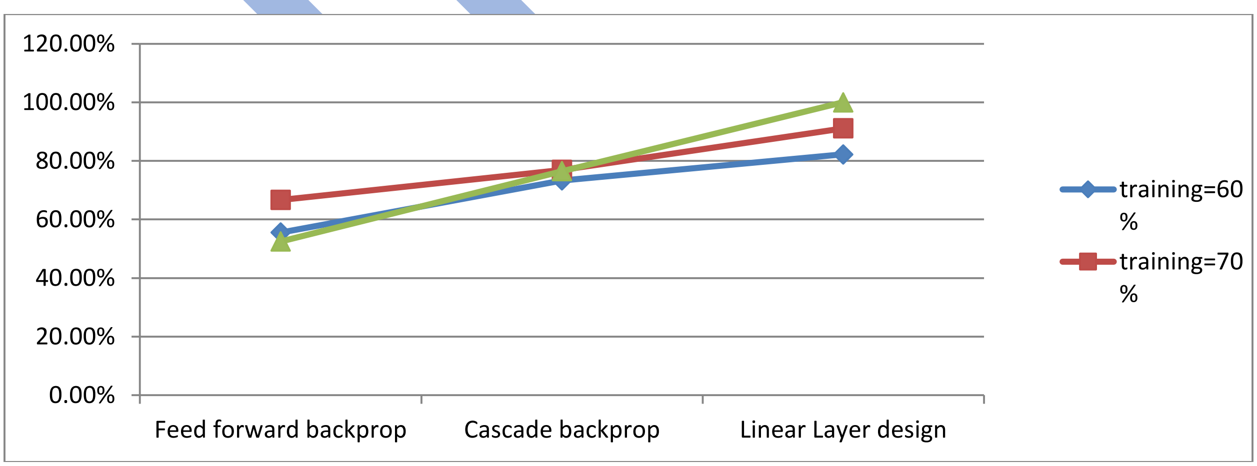


Fig 6 : Accuracy of different Neural Networks

 

| NAME OF CLASSIFIER | TYPES | TRAINING=60% TESTING=40% | TRAINING=70% TESTING=30% | TRAINING=85% TESTING=15% |
|---|---|---|---|---|
| 1. SVM | Linear kernel | 73.3% | 75% | 87.5% |
| | Quadratic kernel | 66.7% | 64.3% | 81.3% |
| | Cubic kernel | 60.0% | 67.9% | 75% |
| | Fine Gaussian kernel | 46.7% | 60.7% | 68.8% |
| | Medium Gaussian kernel | 62.2% | 60.7% | 68.8% |
| | Coarse Gaussian kernel | 64.4% | 60.7% | 75% |
| 2. K-NN | Fine K-NN | 60.0% | 60.7% | 68.8% |
| | Medium K-NN | 57.8% | 57.1% | 68.8% |
| | Coarse K-NN | 37.8% | 39.3% | 37.5% |
| | Cosine K-NN | 53.3% | 53.6% | 50.0% |
| | Cubic K-NN | 55.6% | 53.6% | 68.8% |
| | Weighted K-NN | 60.0% | 57.1% | 81.3% |
| 3. DECISION TREES | Complex Trees | 44.4% | 64.3% | 62.5% |
| | Medium Trees | 44.4% | 64.3% | 62.5% |
| | Simple Trees | 53.3% | 67.9% | 68.8% |
| 4. NEURAL NETWORKS | Cascade backprop | 73.33% | 76.92% | 76.47% |
| | Feedforward backprop | 55.55% | 66.66% | 52.94% |
| | Linear layer | 82.22% | 91.11% | 100% |

Table 3: Accuracy of different classifiers with different functions

**Artifical neural network** – from various ANNs available , Feed forward Back propagation , Cascade Back propagation and Linear Layer design ANNs are used and the results produced are plotted in fig 6. Linear layer design ANN gave 100% accuracy when 85% of data was used for training.

Table 3 depicts the accuracy values achieved by different classifiers used across the proposed system with different functions of each of them.

## 6. CONCLUSIONS

This paper proposes algorithm that grades the guava fruit into four categories ( unripe, ripe, overripe and defected) based on color, shape, size and texture features. For texture features, we have successfully implemented Local Tetra patterns. Features extracted are classified using SVM, K-NN, Trees, ANNs and Ensemble Classifiers. Experimental results showed that all classifiers performed better when maximum data is used for training. 100% accuracy is achieved by Linear Layer Design Neural Network. Future scope may be to decrease the computational time to process and to classify the input images. The proposed algorithm can be used for other spherical fruits or vegetables.

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