Multimedia Tools and Applications (2023) 82:39525–39550
https://doi.org/10.1007/s11042-021-11616-2

1216: INTELLIGENT AND SUSTAINABLE TECHNIQUES FOR MULTIMEDIA BIG DATA MANAGEMENT FOR SMART CITIES SERVICES

Deep grading of mangoes using Convolutional Neural Network and Computer Vision

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Received: 24 November 2020 / Revised: 1 June 2021 / Accepted: 22 September 2021 / Published online: 14 July 2022

Abstract
The grading of mangoes is an essential aspect of providing quality fruits to consumers and control the needs of the fruit processing industry. Manual visual inspection leads to inconsistencies, and it is human labour intensive. This paper is focused on improving the accuracy of the automatic mango grading system by doing multi-level grading using Deep Learning, Computer Vision and Image processing techniques. The proposed system is based on the mango maturity ripening stage, shape, texture features, colour and defects to identify the mango variety and classify based on quality. The maturity ripening stage of the mango is extracted using the Convolutional Neural Network (CNN). Computer Vision and Image processing techniques are used to extract shape, texture features and defects. The extracted features are input to the Random Forest classifier to identify the mango variety and grade the mango quality into three classes Notfit, Average and Good. The system has been validated on the dataset created for this study across three different varieties, Banganapalli, Neelam and Rumani, the most popular in Tamil Nadu. The proposed system using features extracted from CNN enhanced the system's efficiency with an accuracy of 93.23% for variety recognition and 95.11% for quality grading. Hence the proposed system is fully automated, commercially viable and has improved accuracy in variety recognition and quality grading of mangoes across different varieties.

Keywords Deep learning · Computer vision · Image processing · Classifier · Accuracy · Grading · Variety · Random forest · Convolutional neural network

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1 Introduction

The acreage records show that Indian Horticulture has grown exponentially over the years, and the fruits and vegetable production has surpassed the country's food grain production. According to the Farm Ministry news 2021, the Mango production in the country is estimated to increase by 4.24% to 21.12 million tonnes in the crop year 2020–21 ending June. Mangoes are grown in almost all states, and India occupies one of the top positions in total production among Mango exporters. According to the Agricultural and Processed Food Products Export Development Authority (APEDA), India is home to more than 1000 different mangoes. Around 30 varieties are grown commercially for export business (APEDA database, 2020). Neelam, Bangalora, Alphonso, Rumani, Banganapalli are some of the tropical mango varieties grown abundantly in Tamil Nadu and present an excellent potential to export mangoes to various European countries. To export mangoes of good quality and for mass consumption of the food processing industries, there should be a uniform way to grade and sort the mangoes based on their quality.

Mango fruit quality needs to be measured at all stages of ripeness from 'hard green' to 'commercial ripe' to 'eating ripe' and at every stage of the supply chain from farmer to the retail shelf. So, ripeness of mango is an essential indicator of mango grade quality. Besides, the assessment for quality and grading is done based on other visible characteristics like the spots, rots, bruises, irregular shape, and wrinkles that appear on the surface, commonly called defects during post-harvest handling. The mango assessment is done manually in their warehouses, which is high cost, laborious and inconsistent due to high subjectivity and has to be done to improve customer acceptance rate and avoid the rest of the produce getting contaminated.

Banganapalli mangoes are harvested and available in plenty from April to June. Neelam and Rumani are harvested towards the end of the Banganapalli season and are available in the market till August. Fruit quality can be measured differently at a different stage of ripeness. Typically, mangoes are harvested when mature on the tree but not ripe or soft. The colour of mature fruits turns from green to yellow as an indication of ripening, and the shoulder becomes well developed at the stem end of the fruit. Mature Banganapalli mangoes are firm with broad shoulders, round cheeks and have the right flesh colour. They are generally large-sized, oval and are golden yellow. Neelam is medium-sized mangoes ovate-oblique in shape, and the skin of ripe mango is in saffron yellow colour. Rumani mangoes are juicy in texture and called ice cream mangoes, round in shape and greenish-yellow in colour.

Nearly 8–18% of the fruits and vegetables go wasted during post-harvest handling, according to APEDA 2021 agriculture export policy. This wastage can be avoided by scientific methods, which can identify the right stage to harvest. It is a general practice to harvest mangoes (immature mangoes) early to capture the market. Such immature mangoes lose their taste and flavour, and over mature mangoes do not last long or have a short storage shelf life. So, it is essential not only during harvest but also during post-harvest to identify the fruit ripening stage, the quality grade to decide on which mangoes to export and which ones to consume locally.

The main contributions of this paper are summarised as follows.

- Proposal to use multi-level grading for variety recognition and grade quality classification.

- A model to assess the maturity ripening stage of mango varieties using a novel Conventional Neural network (CNN) architecture. The model works well for the labelled image 'Ripe-Stage' dataset created for this study. The model will classify the mango into one of the four stages Raw, Early Ripe, Partial Ripe and Ripe, and identify the subtle differences in the in-between stages with reliable accuracy.
- Extract defects and shape, colour and texture, features using computer vision and image processing techniques. Recognize the mango variety based on ripening stage, shape, colour and texture.
- Study of five different classifying algorithms for their suitability to recognize the mango variety and classify according to quality grade.
- Classify the grade quality based on ripening stage, shape, texture, colour, and defects into three categories: NotFit, Average, and Good quality.
- 'Ripe-Stage' dataset of 12,168 mango images for four ripening grade stage was created.
- 'Variety-Quality' dataset of 1328 mango images for three varieties was created.

Such a system will be automated and be of immense help from farmers to retailers and consumers in providing a quality product across the value chain. The following are the sections that are discussed in this paper. Section 2 is on Literature Review. Section 3 describes the image acquisition process, the proposed system methodology, the grade stage detection, image processing techniques for feature extraction, and the various classifiers for grading. Section 4 on results and discussion, and Section 5 concludes with the next steps and future scope.

2 Literature review

Computer vision-based systems are widely used for automatic quality inspection and grading of fruits. As a first step, the image is pre-processed, followed by image segmentation and feature extraction using Image processing techniques. Feature extraction is done based on selecting the most significant parameters that impact the quality during harvest time. Based on the features extracted, the grading of the quality of the fruit is done. Many methods are proposed to classify and grade mangoes based on appearance/physical and chemical parameters. However, most of them are either laborious or involve destructive techniques.

2.1 Related work

Image processing methods extract the colour RGB / HSI features from images by pre-processing, resizing, removing the background, cropping the images. Nandi, C. S. and Koley, C. (2014) did automatic sorting and grading mango fruits using a computer vision-based system. The authors used size, maturity level and fuzzy logic for consistent grading and uniform sorting [13]. The Gaussian Mixture Model (GMM) was used to predict the maturity level, and the size was calculated from the binary image of the mango fruit. The mangoes were graded into four different grades, only using size and maturity level as parameters. The performance was around 88% to 90% for the different grades and matched closely to the results of the manual experts. Ganiron Jr (2014) measured the size, roundness and percentage of defects on the mango for grading the mango as export quality, local, or reject [4]. The features size, shape, and defects were extracted using an image processing algorithm and input to the kNN classifier for grading based on quality. However, the system classified mangoes with green stem pixels as healthy and mangoes with brown stem pixels as defective.

Vyas, M. et al. (2014) used colour and size and spot features to grade mangoes into four grade classes [10]. The authors used rule-based grading of Totapuri and Badami mangoes and graded them into Grade 1, Grade 2, Grade 3 and Reject with an average accuracy of 94.97%. The colour feature was extracted using the Lab colour model. The major axis determines the mango size, and the spots were extracted from the whole surface of the mango.

Salunkhe R. P. and Patil A. A. (2015) used RGB and HSV colour model and performed a rule-based classification of Alphonso mangoes into three grades [12]. The authors graded the mangoes as Unripen, Ripen and Fully Ripen grades with 90.4% accuracy using the RGB model and 84.2% accuracy using the HSV model. The image's red, green and blue components are extracted to determine the ripening stage in the RGB model. In the other approach using HSV model, the hue saturation value map is analyzed for detecting the ripening stage.

Khoje, S. (2017) performed mango size grading using various size estimation metrics and used two classifiers, namely, Feed Forward Neural Network (FFNN) and Support Vector Machine (SVM) in grading according to the CODEX size standards [21]. The authors achieved 97% accuracy for size-based grading. Momin, M. A. et al. (2017) developed a complete machine vision system that graded mangoes based on their mass into large, medium and small by extracting features like projected area, perimeter and roundness [9]. The authors achieved an accuracy of 97% using features projected area and Feret diameter and 79% using the perimeter feature and 36% for roundness feature. The authors found a direct relationship between mass to the projected area, Feret diameter and perimeter but not with roundness.

Supekar, A. D., & Wakode, M. (2020) graded Dasheri and Kesar mango varieties into four grades based on ripeness, size, shape and defect with an accuracy of 88.88% [23]. Image processing was used to extract the features and input them to the Random Forest for classification. The authors classified the mango ripeness as unripe, mid-ripe and ripe, size as small, medium, large and shape as well-formed, deformed categories. The author used K-means clustering to classify mango defect as non-defective, mid-defective and completely defective. Using these categories, the author then applied formula grading rules for final grading.

Kamel, R. M. (2015) classified tomatoes using different colour models like RGB, HSV, CIE L*a*b to create a combined colour feature vector input to Artificial Neural Network (ANN) classifier that determines the maturity grading based on colour with an overall accuracy of 97.9% [17]. The authors used twelve colour features as input to the ANN classifier. The author graded tomatoes as green, red and pink classes using the L*, a* and b* colour spaces.

Widiyanto, W. W., Purwanto, E. and Neighbor, K. (2019) graded the mangoes into three Super, A and B Classes [24]. The authors used Computer Vision based on the characteristics of GLCM texture and kNN as the classification algorithm. The authors achieved an accuracy of 88.88%. The authors found that the kNN algorithm with k value 9 gave the best accuracy.

In all the above works, the quality grading of mangoes or other fruits was done using a single parameter like colour/texture or based on a few parameters like shape, size and defect. The image processing and computer vision techniques cannot do the fine-grain classification of the maturity ripening stage. They will not distinguish the subtle changes in the in-between maturity ripening stage. The classification accuracy will improve if multiple parameters like maturity stage, size, shape, defects, texture and colour are considered for classification and grading.

The advances in artificial intelligence and deep learning have seen breakthrough advances in vision-based feature extraction to overcome the challenges in computer-vision-based grading and will be able to identify the subtle in-between changes in the maturity stage of the fruit. Convolutional Neural Network (CNN) is a deep learning architecture used for image classification and is used successfully in fruit identification and fruit classification using pre-trained architectures. CNN architectures extend the classical Artificial Neural Network (ANN) by adding more depth in layers into the network that allows various convolutions on the data for a more meaningful extraction of features.

Z Li, F Li, L Zhu et al. (2020) used pre-trained model VGG-M network for vegetable recognition based on vegetable images classification with an accuracy of 92.1% [11]. The model was trained on five categories of vegetables: broccoli, pumpkin, cauliflower, mushrooms and cucumber. The images used for training was obtained from the ImageNet dataset.

Zhang, Y. et al. (2018) used a novel convolutional neural network architecture to classify the banana ripening stages [27]. The model was trained using the global and local features of the banana image. The author used 17,312 images of bananas in different ripening stages to identify the different stages. The classification was a fine-grained classification into 7 or 14 different ripening categories with a precision of 95.6% and 93.5%, respectively. Yossy, E. H. et al. (2017) developed a system based on an artificial neural network, computer vision and C language to detect if the mango is ripe or unripe with 94% accuracy [26]. The authors chose Gincu mango because it has good colour distribution and used the colour feature to classify Gincu mango as ripe and unripe. The computer vision system is used to extract the features and input them to the feed-forward neural network to determine the size of the mango and the ripeness category.

Kamble, P. R. et al. (2020) used CNN to identify if the fruit is raw or ripe from the fruit image [8]. The authors did it for three different types of fruits mango, banana and apple, using a pre-trained network like VGG16. They achieved 92% accuracy in classifying mango fruit as raw or ripe. Srinivasan, D. and Yousef, M. (2020), using the pre-trained ReNnet-50 CNN model, could classify if the apple fruit is fresh or rotten with about 97.92% accuracy [20]. The authors used 5031 images for classification, with 2088 images for fresh apples and 2943 for rotten apples.

S. K. Behera, A. K. Rath and P. K. Sethy. (2020) used pre-trained model VGG19 to identify papaya fruits' maturity status into three maturity stages: immature, partially mature, and mature [2]. The authors have used a transfer learning approach and got an accuracy of 100%.

Naik, S. (2019) used CNN to train on the shape, size and maturity parameter of mango and based on these parameters, a decision on mango grading was taken [18]. The author used labels deformed and well-formed for shape, small, medium, big for size, ripe, partially ripe, and unripe for maturity. The author has compared four different CNN architecture models, namely ResNet, MobileNet, v4, and Xception and found that MobileNet performed the best with an accuracy of 83.97%. The author used SVM for classification using the above features.

Altaheri et al. (2019) used pre-trained AlexNet and VGG-16 to classify date fruit bunches based on type, maturity and harvesting decision using harvesting robots [1]. The model was trained on a dataset with over 8000 images of more than 350 date bunches. The dataset required no pre-processing of images. The model achieved an accuracy of 99.01%, 97.25%, and 98.59% with classification times of 20.7, 20.6 and 35.9 ms for the maturity, type and harvesting decision, respectively, using the VGG-16 model.

The CNN architectures used in the above works used pre-trained networks for maturity ripening stage detection and grading. According to Naranjo-Torres, J et al. (2020), 70% of the agricultural applications use pre-trained networks [14]. The main reason is that the agriculture domain uses CNN as a support function in fruit recognition and grading areas. The pre-trained network has its disadvantages and requires frequent optimization when used in fruit grading applications.

The success of the Convolutional Neural Network lies in the quality of the dataset used for training. The larger the dataset, the higher the probability of correct classifications. The main disadvantage of CNN is that it takes longer to train and requires more computing power to train on large datasets. Also, creating a sizeable labelled dataset requires a dedicated time of domain experts, and the precision depends on the quality of labelling. The other main disadvantage is that using pre-trained networks on small dataset results in optimization issues because of the complexity of the pre-trained models.

2.2 Contribution

In this study, to overcome the limitations of any single grading method, a combination of methods is used for grading. The multi-level grading of mangoes is done using CNN, image processing and computer vision methods. Quality grading of mango into NotFit, Average and Good is done based on multiple feature sets that include ripeness maturity stage, colour, shape-based features, GLCM based features, and defects to improve grading accuracy. CNN was used to extract the ripeness maturity stage of mango to improve the overall accuracy of the mango quality grading. This study also compares five different algorithms Naïve Bayes, K Nearest Neighbor, Support Vector Machine, Linear Discriminant Analysis and Random Forest for variety recognition and quality grade classification based on the above features.

This study is a continuation of the previous research work on mango maturity ripening stage grading based on the skin cuticle structure using Convolutional Neural Network (CNN). Two varieties, Banganapalli and Killimooku mango images were used to train the CNN and the model achieved an accuracy of 83% based on skin texture-based classification [6]. A detailed review was also done on different maturity indices used for quality grading using machine learning and deep learning techniques [5].

3 Materials and methods

The main objective of designing an intelligent mango quality grading solution is to establish consistency in grading and increase the accuracy of identifying good quality mangoes in a non-destructive and cost-effective manner. Such a solution will reduce the laborious manual cost, ensure consistency and increase export efficiency.

3.1 Methodology & architecture diagram

The methodology of mango fruit grading has an (a) image acquisition kit comprising of a mobile phone camera and photo studio lightbox (b) Convolutional Neural Network (CNN) model for assessing the ripening maturity grade of the mango (c) Pre-processing and

Table 1 Mango grade quality characteristics

Grade quality	Characteristics
NOTFIT	These are mangoes that are not fully ripe, namely raw or early ripe Alternatively, mangoes ripe or overripe and have many surface defects like rot are also not fit for consumption
AVERAGE	These are ripe or nearly ripe mangoes with very few surface defects, immature ripe, irregular size, not uniformly ripe, and the average eating quality. These are fit for local market consumption where the market is more price-driven than quality
GOOD	These are perfect ripe mangoes with no external defects, possess the proper shape, size, colour, and shoulder development and are of good eating quality and can be considered for external export markets

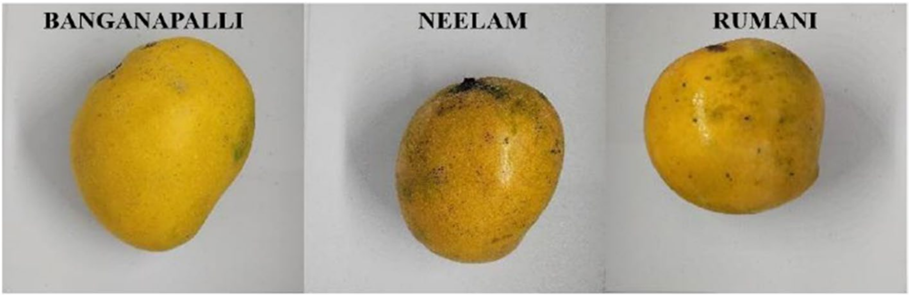


Fig. 1 Ripe mango varieties

Feature Extraction using image processing and computer vision techniques (d) Classifier based on machine learning algorithm for variety recognition and quality grading.

According to their ripening stage, the 'Ripe-Stage' mango dataset is classified into four different maturity stages RAW, EARLYRIPE, PARTIAL RIPE, and RIPE. This ripening stage and other features extracted using image processing techniques are input to the classifier for mango variety recognition and mango quality grading. The same image dataset was then quality graded manually by a couple of expert farmer/retailer into three classes: NOTFIT, AVERAGE, and GOOD. Their quality characteristics are broadly based on grade stage, size, shape, appearance, colour, visual defects, texture and are represented in Table 1 as follows.

Mangoes of 3 different varieties Banganapalli (BA), Neelam (NL) and Rumani (RU) were collected from two different local farms in Tada near Chennai and a few retail stores in Chennai. Banganapalli mangoes were first collected, and randomness was ensured by mixing the mangoes from the farm and retail stores for analysis and further processing. Once the Banganapalli season ended, Rumani and Neelam mango season started, and a similar process was followed. For quality assessment, the opinion of two human experts in the related agricultural field was taken for manual identification of the ripening stage of the mangoes, recognize the variety and grade the quality of mango. Sample images of the three ripe mango varieties as identified by the expert from the mango dataset is shown below in Fig. 1.

The automated variety recognition and quality grading of mangoes are broadly divided into two stages in the proposed work. The first stage determines the ripening maturity

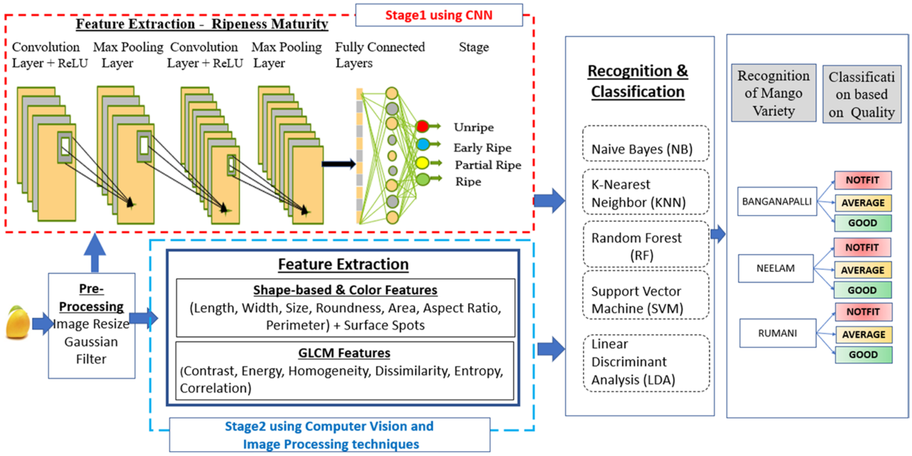


Fig. 2 Architecture diagram

Table 2 Mango image dataset

Type of Grading/ Dataset Name	Total no of images	Mango Varieties	Source
Maturity Ripening Stage / 'Ripe-Stage' dataset	12,168	Banganapalli, Rumani, Neelam	Tada Farm near Chennai and Retail Stores
Shape, Texture & Colour / 'Variety-Quality' dataset	1328	Banganapalli, Rumani, Neelam	Tada Farm near Chennai and Retail Stores

grade of the mango using a convolutional neural network. The second stage extracts the colour, shape-based and texture features using image processing and computer vision techniques. Combining all the above features is input to the classifier to identify the mango variety and classify the mango grade quality as per the characteristics defined in Table 1. Figure 2 shows the architecture diagram of the overall methodology with two stages.

3.2 Image acquisition

The mangoes were kept in a white studio box which is well lit using LED lights on all sides, and the image is captured in JPEG format using a mobile phone camera without any shadow. All images have a plain white background taken at a distance of 30 cm, and they are cropped to a standard boundary marked on the white studio box and can be taken any time during the day or night. The mango dataset created for this study is as shown in Table 2.

Different techniques are then performed on the mango image dataset to extract the colour, shape, texture, defects and ripening maturity stage features. The colour of the mango fruit has a strong influence on customer desirability and freshness. The size and shape impact the pricing, and the texture is an indicator of the mango fruit internal quality. The shape features are extracted using the mango fruit geometric characteristics, and Gray Level Co-occurrence matrix (GLCM) is a statistical-based approach for extracting texture features. In Fig. 3 are images of ripe Banganapalli, Neelam and Rumani variety of mangoes graded by the manual expert from the image dataset created for this study.

3.3 Feature extraction using computer vision and image processing

The mangoes are captured in the RGB colour space. The images are then resized to a fixed resolution JPEG of 256X256 pixels. Then the following pre-processing steps are applied to segment the mango image.

3.3.1 Pre-processing

As a first step in pre-processing the images, a grayscale transformation is done to convert the RGB image to a grayscale image followed by an 11 * 11 Gaussian blur filter, which is applied to reduce the image noise. Edge detection identifies the mango fruit edges by considering the sharp intensity changes at the edges. The edge detection is done using a canny edge detector to determine the vertices to segment the mango image from the background. The canny image has used a mask in the original mango image to subtract the background from the mango image. The resultant image is the segmented mango image without the background pixels, as shown in Fig. 4 below.

3.3.2 Geometric or shape features

Shape Features are measured by roundness, aspect ratio, area, perimeter, size, width and length of the mango image based on standardized formulas. The major and minor length is the number of pixels along the longest and shortest diameter of the ellipse (mango

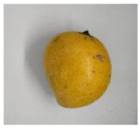
Mango Variety	NOTFIT	AVERAGE	GOOD
Banganapalli			
Neelam			
Rumani			

Fig. 3 Mango Quality Grading Images according to their variety

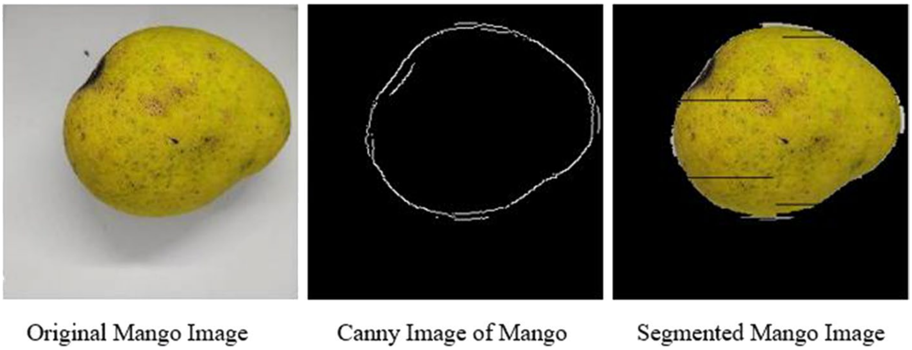


Fig. 4 Pre-processing results of the Banganapalli mango image

shape is assumed to be like an ellipse), as shown in Fig. 5 below. The aspect ratio is the ratio of major to minor length, which indicates whether the fruit is of regular shape or misshapen and whether the mango fruit shoulders are broad and well developed or narrow and underdeveloped. The aspect ratio is calculated as in Eq. (1).

$$\text{Aspect Ratio} = \text{Length of Major Axis} / \text{Length of Minor Axis} \tag{1}$$

In this study, for the Banganapalli mango, if the aspect ratio is above a threshold value (T), the mango is said to have broad shoulders. Different ranges have been fixed for the different shoulder types: Narrow, Medium and Broad shoulders. In this study, for Banganapalli mangoes, the T value for broad shoulders is in-between 0.8 and 1.2.

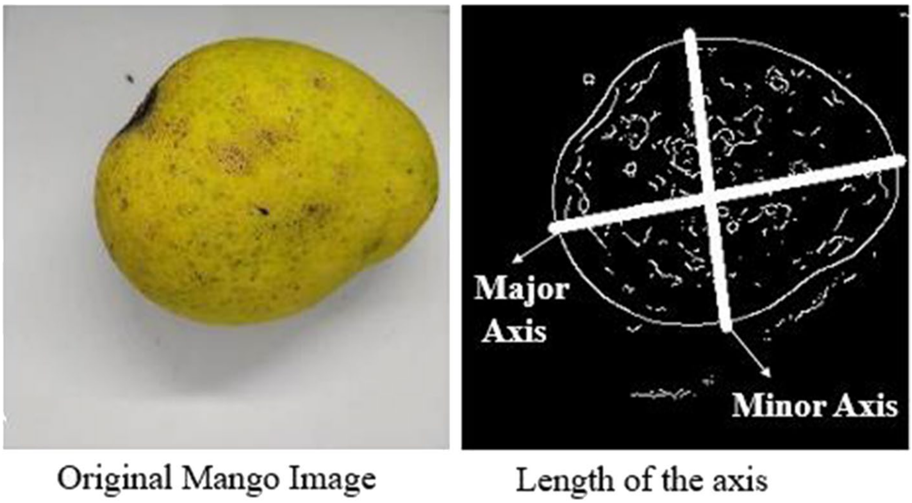


Fig. 5 Length of the major and minor axis of Banganapalli mango

The size feature is estimated by calculating the area covered by the mango image. The total number of pixels that cover the image is counted, and size is estimated and categorized as small, medium and big. The size is calculated as in Eq. (2) shown below.

$$\text{Area} = \text{pi} * ((\text{Major Axis Length}/2) * (\text{Minor Axis Length}/2)) \tag{2}$$

The roundness ratio of the area to its maximum diameter indicates whether the mango fruit has fully developed cheeks, i.e., round cheeks or narrow cheeks. The roundness is calculated as in Eq. (3) below. In this study, for Banganapalli mangoes, if the roundness % is greater than 98.21%, then the mango shape is round. The ranges for narrow and oblong shape are also determined by calculating the roundness %.

$$\text{Roundness}\ (\%) = (4\text{pi} * \text{Area}) / \left(\text{Perimeter}^2\right) * 100 \tag{3}$$

3.3.3 Spots or defects

The number of black spots is an indicator of whether the fruit is deceased. The number of black pixels in the mango area is taken as spots. The ratio of spots to total mango pixels is computed to determine whether the spot ratio is beyond a threshold value to classify the mango as diseased and not fit for consumption. The mango is classified as mango with no spots, mild or few spots, and numerous spots based on the spot ratio. The defective spots ratio is calculated as shown in Eq. (4) below.

$$\text{Defective Spots Ratio}\ (\%) = (\text{No ofBlackSpot Pixels} / \text{Total pixels}) * 100 \tag{4}$$

In this study, the threshold was fixed at 7% for numerous spots. So, if the defective spots ratio is greater than the threshold value, then the mango is classified to have numerous spots and diseased, as shown in Fig. 6 above. Similarly, the range has been determined for mangoes with no spots and mild or few spots.

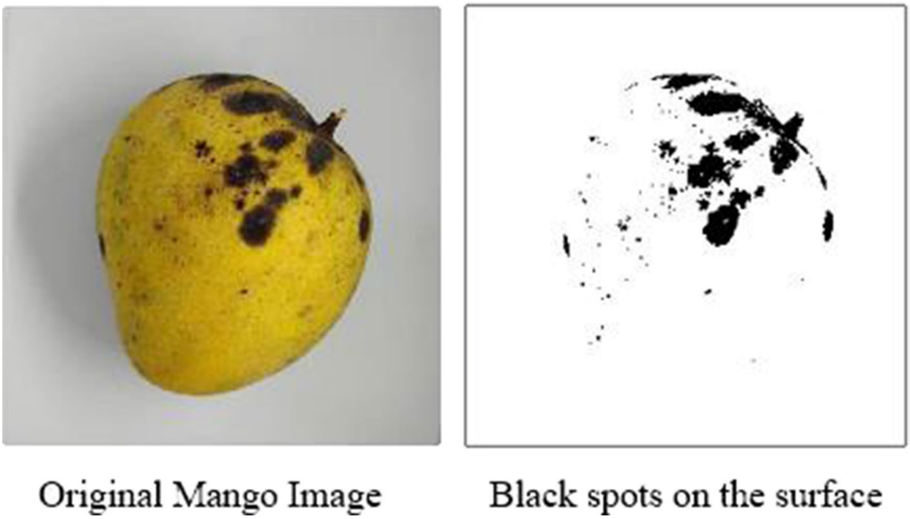


Fig. 6 Defective spots in Banganapalli mango

Table 3 CIELab values for mango external colour

Mango variety	Mango stage	CIELab values
Banganapalli	Ripe	L – 66.84 ± 2.14, a – 11.01 ± 2.7, b – 51.43 ± 2.0
Neelam	Ripe	L – 60.9 ± 2.07, a – 23.01 ± 2.83, b – 51.86 ± 3.0
Rumani	Ripe	L – 52.35 ± 3.52, a – 19.0 ± 2.63, b – 51.0 ± 3.60

Table 4 Equations to calculate GLCM feature extraction

Contrast $= \sum_{i,j} P_{i,j}(i-j)^2$	Homogeneity $= \sum_{i,j} \frac{Pi,j}{1+(i-j)^2}$
Energy $= \sum_{i,j} Pi,j^2$	Dissimilarity $= \sum_{i,j} P_{i,j}\lvert i-j\rvert$
Entropy $= \sum_i \sum_j \lvert i-j\rvert p(i,j) log_2 p(i,j)$	Correlation $= \sum_{i,j} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma_i \sigma_j}$

3.3.4 Colour features

The colour is an important feature to measure the freshness of the mango. The CIElab colour space is being used to determine the peel colour where L is the measure of Lightness, a and b indicates the changes in the ratio of red/green and green/blue, respectively. The cropped image is converted from RGB to Lab colour space, and the mean of the L, a, b values are measured to determine the overall colour of the fruit. Sapan Naik and Bankim Patel (2014), for grading mango based on maturity, used CIEL*a*b colour space and achieved an accuracy of 94% using the dominant colour method [19]. In this study, based on the mango variety, the Lab values indicate whether the fruit is dull or dark green for a raw mango to different shades of yellow, orange, and deep orange for ripe and overripe mangoes. The CIElab values for the different variety of mangoes are shown in Table 3 below.

3.3.5 Statistical or texture features

Texture characteristics are based on the intensity variation of the grey pixels in the image. GLCM matrix is a matrix tabulation of how often the different intensity levels of grey occur together in the image. Since there are so many textural features with different dimensions and are not all independent, choosing the minimal set of right textural features for classification is essential. The statistical features extracted in this study are homogeneity, contrast, energy, entropy, correlation and dissimilarity. Contrast measures the changes in the intensity of neighbouring pixels, reflecting the change in the intensity contrast between the neighbouring pixels. Homogeneity is a closeness measure of the pixel distribution in the GLCM matrix to the GLCM diagonal. Correlation is measured as the linear dependency of grey pixel levels to the levels of adjacent neighbouring pixels. Energy is a measure of the intensity distribution of pixels against the range of grey levels. Dissimilarity is a measure of the distance between pairs of pixels in the mango image region of interest. Entropy is directly proportional to the homogeneity of the fruit and measures the randomness of the pixel element. The grey level co-occurrence matrix is calculated using graycomatrix from skimage library of python and the formulas as shown below in Table 4

P is the grey-level co-occurrence histogram to compute one of the specified properties indicated in Table 4.

3.4 Feature extraction using convolutional neural network (CNN)

The CNN model needs images of the fixed resolution, so the images are resized as mentioned in the previous subsection to a resolution JPEG of 256X256 pixels. This resizing also ensures that the computational time taken by the CNN model is optimal. The mango dataset was augmented to 12,168 images for training, validating and testing the model and preventing any model overfitting issues. The different augmentations done to the images are random image rotations, randomly flipping images vertically or horizontally, increasing the contrast of the images, image scaling, performing affine transformations, and introducing random noise.

3.4.1 Model architecture

The resized images are given as input to the CNN model with multiple hidden layers and an output layer, a class label indicating the different ripening stages. There is a feature extraction layer with four convolutional modules and two fully connected layers with a softmax algorithm for classification. The convolutional module applies filters to the input feature map and results in a new output feature map. An activation function called rectified linear unit (ReLU) is applied to introduce nonlinearity into the model. The convolutional module is then followed by MAX pooling layer and a dropout layer. The pooling layer reduces the dimensionality, and the dropout layer reduces the chances of overfitting. The convolutional neural network architecture with the convolutional modules, MAX pooling, dropout and dense layers is as shown in Fig. 7

3.4.2 Tuning the model

The mango dataset is split as 60:20:20 with 60% of images used for training, 20% for validation and 20% for testing. After training, the model is validated using the validation dataset, separate from the training set. The model is then saved along with the weights for further prediction of the testing data set. Once trained, the network can predict the stage of any new input mango image data and distinguish the in-between stages very effectively.

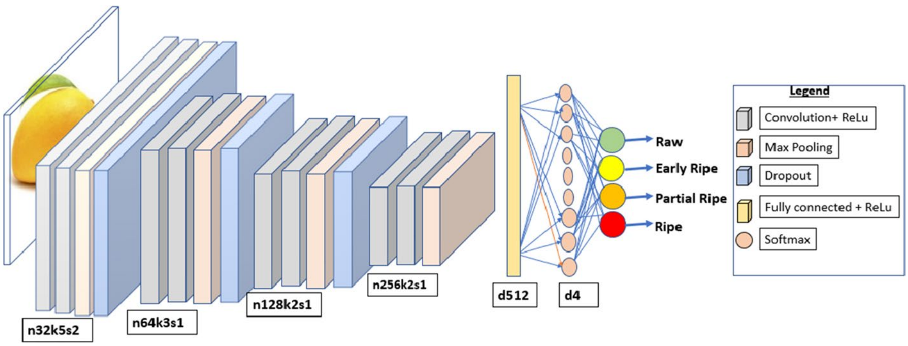


Fig. 7 Convolutional neural network diagram

The hyperparameters such as the kernel size, filters, stride, dropout rates, learning rate and the number of epochs are tuned to achieve maximum accuracy.

The model has an input layer, eight hidden layers, four pooling layers and two fully connected dense layers. The first convolutional model uses 32 kernels of dimension 5×5. The second, third and fourth convolution module has 64, 128, 256 kernels of dimension 3×3, respectively. Size of two and stride two is applied in the MAX pooling layer to reduce the number of parameters that the model needs to learn. A dropout regularisation of 10% is applied after each of the convolutional modules. The dropout is to reduce overfitting and also improve the performance of the model. The network is optimized using Adam optimizer with loss type as 'sparse categorical entropy'. A weight decay regularization of 0.0001 was applied to the sparse categorical entropy loss function to reduce overfitting. The batch size chosen for this model was 32, and this ensures a reduction in the memory space required and speeds up training. The last layer of the model uses a softmax classifier to classify the mango into four stages: Raw, Early Ripe, Partial Ripe, and Ripe.

The model was trained on high-performance CPUs using Keras, TensorFlow and Python on Google Cloud Platform. The CNN model took 65 min to run for 50 epochs, resulting in a validation accuracy of 95.8% and testing accuracy of 93.5%. The CNN weights are trained on the dataset created explicitly for this study. Hence, the model had a significant high accuracy and remained constant throughout all the epochs. Sample images of different stages of Bangnapalli mango graded by the CNN are as shown in Fig. 8 below.

3.5 Classifier for variety recognition and quality grading

In this study, five different classifiers, namely Naïve Bayes, k-Nearest Neighbor, Random Forest, Support Vector Machine and Linear Discriminant Analysis, were compared to determine the best-suited classifier for mango variety recognition and quality grade classification.

Naive Bayes classifier is based on the Bayes theorem and is also called the probabilistic classifier. The classifier makes a naïve assumption that the predictors are independent and that the effect of a variable value on a given class is independent of other variables values. Win, O. (2019) used the Naïve Bayes Algorithm to classify different mangoes varieties with about 94% accuracy [25]. Ronald, M. (2016) used Naïve Bayes to classify different apple varieties with about 91% accuracy [16]. In this study, a Gaussian Naïve Bayes classifier is used where the features are assumed to be distributed according to Gaussian distribution.

Fig. 8 Different ripening stages of banganapalli mango variety

k-Nearest Neighbor (kNN) measures the input sample data closeness with the already trained data using a distant metric and does the classification. In this study, the kNN classifier was tested for a k value of 5, which was the most optimum for variety classification and quality grading. De Goma, J. C. et al. (2018) compared kNN, Naïve Bayes, Decision Tree and Bagging to identify fruits based on colour, size, shape and texture. The authors found kNN to perform better, with an accuracy of 81.9% [3].

Support Vector Machine (SVM) is a robust supervised learning algorithm for solving linear and non-linear data classification. SVM finds a linear hyperplane that splits the data with a wide margin into either side of the binary class to improve accuracy. In the case of non-linear data, SVM uses kernel functions to map to a high dimensional space. SVM is used generally for binary class problems, but SVM is extended using near-against-one or one-against-all strategies in multi-class problems. In this study, a multi-class SVM (OVO – One-vs-One) was used, and the SVM was trained and tested with a linear SVC kernel for classification and grading. Pathanjali, C. et al. (2018) compared SVM and kNN in food image classification and found SVM to perform better [15].

Discriminant analysis identifies a subset of features that impact splitting the input data into different classes. Linear Discriminant Analysis maximizes the ratio of between-class variance to the within-class variance in any particular data set, thereby guaranteeing maximal separability. Iqbal, S. et al. (2016) used LDA for colour-based classification of citrus fruits [7].

Random Forest is made up of several decision trees that make a forest, which results in improved accuracy. The training for each decision tree is done separately, and the outcome is averaged to get the resultant output. This process ensures randomness by ensuring the trees are trained on different data sets and use different sets of features to classify. The number of input variables has a vital role in testing the model, and in this study, the number of trees considered is 100. Truong, N. and Long, M. (2020) compared kNN, SVM, RF and LDA to grade mangoes based on external features like length, width, defect and weight and found RF to have an accuracy of 98.1% [22].

4 Results and discussion

As discussed in the previous section, the proposed system has two stages. In stage one, the convolutional neural network is used as a feature extractor to get the mango maturity ripening stage. In stage two, the shape, colour, texture and defects are extracted using image processing and computer vision. These features are input to the classifier for variety recognition and grade quality classification. The algorithm of the proposed system is shown in Fig. 9 below.

4.1 Training the CNN model for feature extraction

The Ripe-Stage dataset consists of 12,168 images of mangoes across the four different ripening labels Raw, Early Ripe, Partial Ripe and Ripe. The mango dataset was split as 60:20:20 with 60% of images used for training, 20% for validation and 20% for testing. The number of images under each label is as shown below in Table 5

The number of epochs was set to 50, and the model was trained using Adam optimizer. The learning rate was set at 0.0001, decay and momentum set to 0.9, batch size to 10. Each epoch took approximately 57secs to complete, and the overall training time for the model

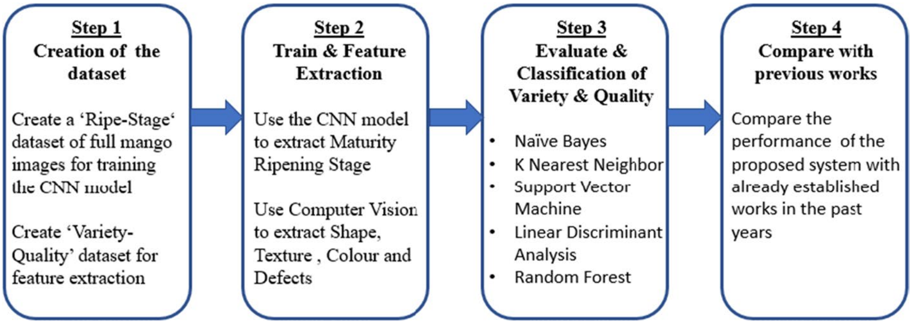


Fig. 9 Algorithm of the proposed system

Table 5 Train Test data split of Ripe-Stage dataset across four stages

Maturity Ripening Stage	Total no of Images	Training Set- 60%	Validation Set—20%	Testing Set – 20%
Raw	2984	1951	505	528
Early Ripe	3057	2001	529	528
Partial Ripe	3020	1977	481	562
Ripe	3107	1951	577	579

was around 65 min. The training accuracy was 99.8, with a loss of 0.7%, and the validation accuracy was at 95.8%, with a loss of 2.0%. The validation and training loss curves are not wide apart, indicating that the model is not overfitting. Also, the validation accuracy stabilized after 20 epochs implying the model is stable. The model is trained well and can distinguish the various ripening maturity stages with very high accuracy and a minimal probability of wrongly classifying. The model was further tested with a test dataset of 2197 images different from the training and validation dataset. The accuracy of the model was at 93.4%, with a loss of 3.3%. The accuracy loss metrics of the testing dataset implies that the model is robust and can work well with unfamiliar data. The loss and accuracy curves for the train and validation dataset are shown below in Fig. 10 & 11.

The CNN model performance is also depicted using the confusion matrix, which compares the predicted category labels to the true labels. The confusion matrix for the test data set of 2197 mangoes across all four ripening grade qualities is shown in Table 6. The diagonal of the matrix below shows the correct classifications, and the rest of the cells indicate misclassification. The Raw and the Early Ripe category has some of the samples incorrectly classified. Similarly, there is an overlap of Partial Ripe samples classified as Ripe. The Ripe category was identified without any misclassification. The overall classification accuracy for the test data set is 93.4%. The results indicate that model is consistent and can identify in-between stages with minimal error.

The model performance was also analyzed using metrics like Precision, Recall and F1 Score and shown in Table 7. Precision, also called the classifier sensitivity, measures how good the model is at detecting the proportion of positives identified correctly, i.e. (raw mangoes identified as raw). The recall value of 94% in Early Ripe indicate there is minimal overlap between ripening grade stages. F1 Score is the Harmonic Mean of Precision and Recall and should tend towards 100% for a good classifier. The AUC

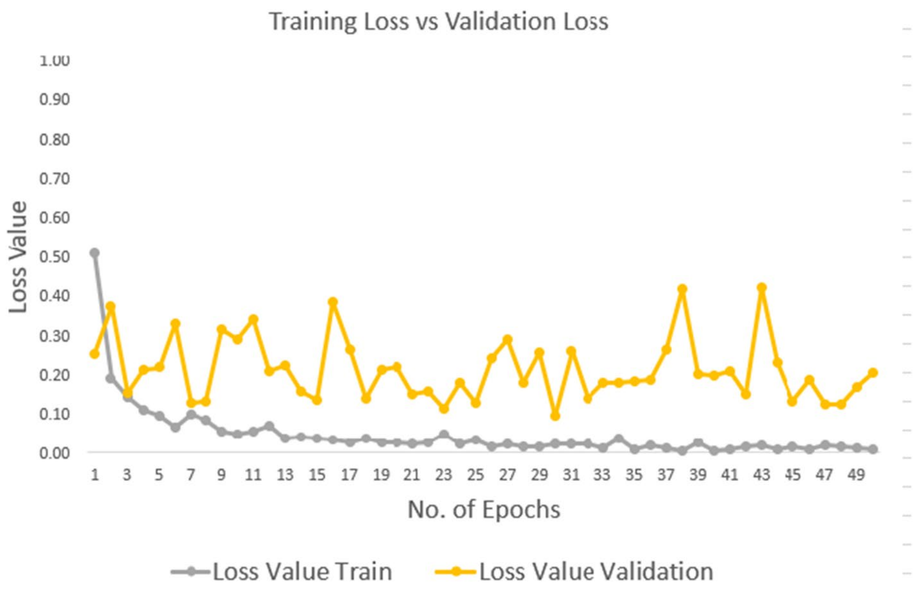


Fig. 10 Loss curves for the convolutional neural network for 50 Epochs

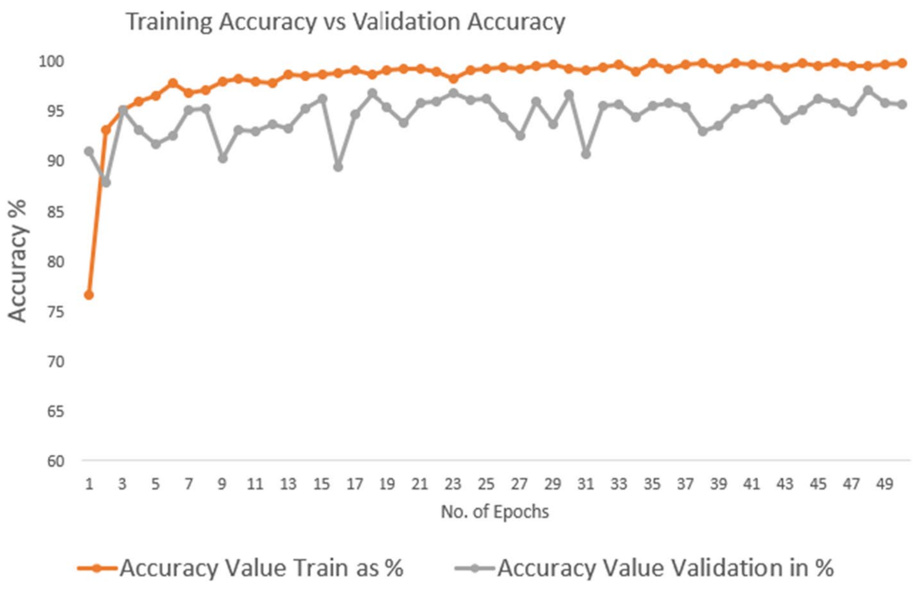


Fig. 11 Accuracy curves for the convolutional neural network for 50 Epochs

for different ripening stages is close to 1, indicating that the model works well for that stage. In Table 7, we see that the AUC curve is above 0.98 for Ripe and 0.94, 0.96 for the EarlyRipe and PartialRipe stages. Thus, we see that the model can also distinguish the in-between stages of ripening with great accuracy.

Table 6 Confusion matrix

Stage		Predicted Class				Classification Error by Category (%)	Classification Accuracy (%)
		Raw	Early Ripe	Partial Ripe	Ripe		
Real Class	Raw	457	70	0	0	13.2	93.4
	Early Ripe	34	493	0	0	6.4	
	Partial Ripe	0	0	521	40	7.1	
	Ripe	0	0	0	578	0	

Table 7 Confusion matrix metrics

Category	Precision (%)	Recall (%)	F1 Score (%)	AUC
Raw	93	87	90	0.9234
Early Ripe	88	94	90	0.9467
Partial Ripe	100	93	96	0.9643
Ripe	94	100	97	0.9876

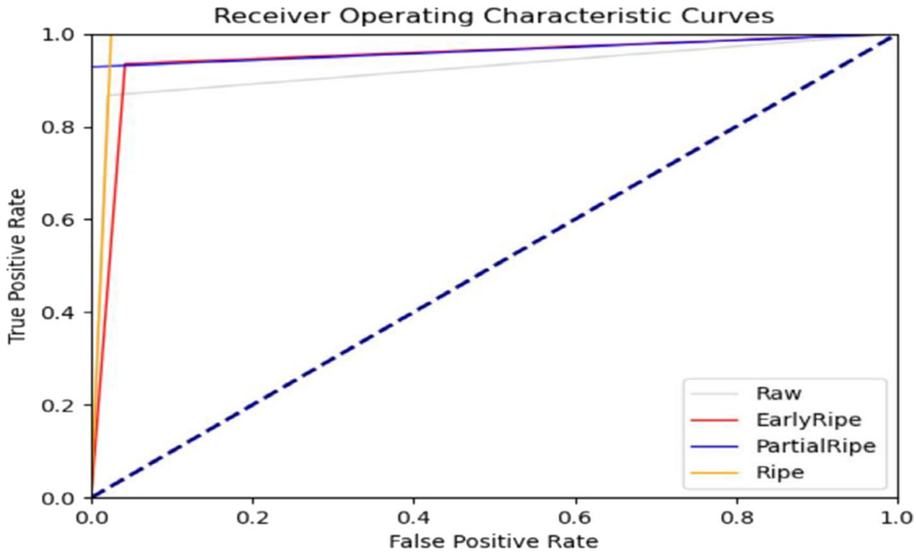


Fig. 12 Receiver operating characteristic curve

The Receiver Operating Characteristics Curve (ROC Curve) and area under the ROC Curve (AUC) is as shown in Fig. 12 below.

4.2 Feature extraction

The Variety-Quality dataset consists of 1328 mango fruit images across three mango varieties Banganapalli, Neelam, Rumani and across three quality grade stages NotFit, Average, Good. The dataset is shown below in Table 8. This dataset is used for feature extraction of stage, colour, shape, texture and defects.

4.2.1 Ripening maturity stage extraction using CNN

The trained CNN model is used to extract the mango ripening maturity stage in the Variety-Quality dataset. The CNN model took approximately 5 min to extract the ripening maturity stage on the Variety-Quality dataset. Naik, S. (2019) used CNN to extract ripening maturity features of Kesar mango with four different pre-trained models (Inception v4, Xception, ResNet50, MobileNet) [18]. The results indicate that the proposed system can identify four ripening stages at a higher accuracy.

4.2.2 Colour and shape extraction

Changes in colour and texture are attributes that influence the different stages of ripening. As outlined in the previous section, the shape features area, perimeter, major-axis length, minor-axis length, roundness ratio, aspect ratio and defects were extracted using computer vision and image processing methods. The CIELab model helps to identify the different colours of the mango according to its ripeness stage. As the mango ripens, the values of L, a and b increases and is also different for different cultivars. Shown below in Fig. 13 is the overview of the image analysis process and feature extraction of diseased mangoes.

4.2.3 Texture extraction

The texture features represent how smooth or coarse the mango surface is, which states whether the mangoes are uniformly ripened or not. The texture features also help in detecting any surface defects on the mango fruit. The features are extracted using the Gray-Level Co-Occurrence Matrix (**GLCM**). The features extracted are homogeneity, contrast, energy, entropy, correlation and dissimilarity. The values of these features of a sample of 45 mangoes across three different quality grades are as shown below in Fig. 14.

From the results, it is seen that a higher value of contrast indicates that the texture of the mango fruit has noise, edges or wrinkles in mango, suggesting notfit quality. Homogeneity measures the smoothness of the grey pixel distribution. Energy represents the uniformity of the texture, and a low value indicates disorders. Entropy indicates the degree of the disorder among the pixels in the mango image. Correlation indicates how perfectly positively correlated the mango fruit image is across all grade qualities. Dissimilarity is high for the mango image, contrasting texture features and is high when the contrast is high.

Table 8 Mango variety-quality dataset

Mango category	NotFit	Average	Good	Total no of mangoes across variety
Banganapalli	352	141	108	601
Neelam	81	312	32	425
Rumani	45	209	48	302
Total No across Quality Grade	478	662	188	1328

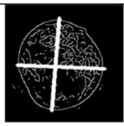
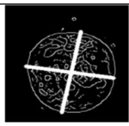
Mango Variety	Original Image	Grayscale transformation	Feature Extracted	
Rotten Banganapalli				
Rotten Neelam				
Rotten Rumani				

Fig. 13 Image analysis and feature extraction process

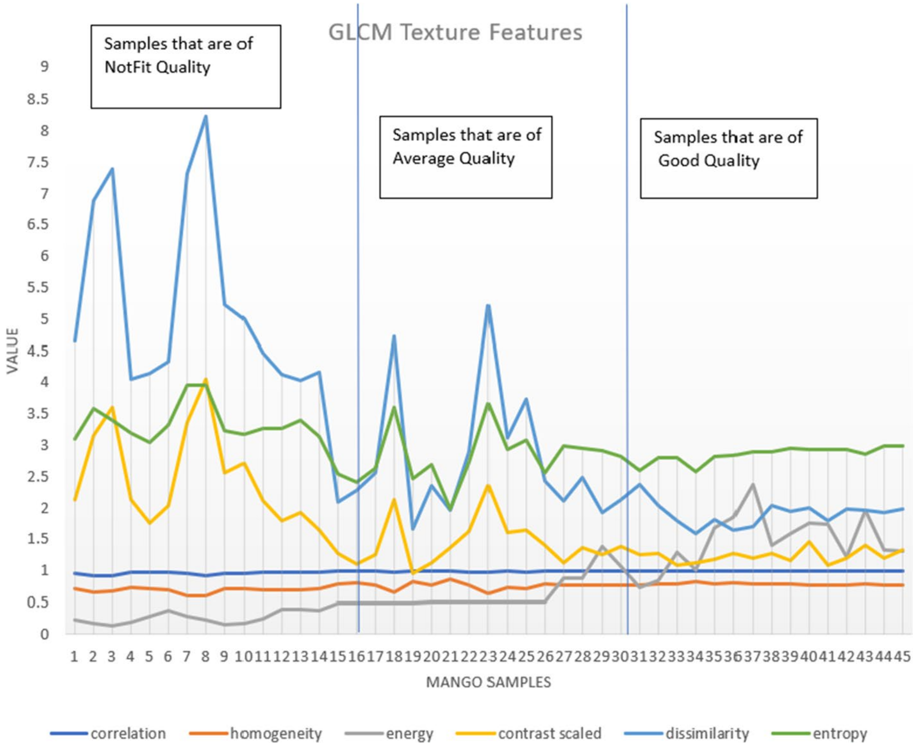


Fig. 14 GLCM texture feature values across all varieties and grade quality

4.3 Variety recognition and quality grading

The extracted shape, colour, grade stage of the mango is used as input parameters to train the classifier to recognize the variety of Banganapalli, Rumani or Neelam. The same combination of features and the texture features and surface defects are input to the classifier to grade the mango quality as NotFit, Average and Good. Their performance was evaluated to determine the best-suited classifier for mango variety recognition and quality grade classification. The chart below in Fig. 15 shows the performance of various classifiers for mango variety grading and quality grading and their average grading accuracy.

It is seen from the results that Random Forest has the highest accuracy in variety recognition and grade classification in comparison to other classifiers. The accuracy for variety is at 93.23%, and that of Grade classification is at 95.11%. The Random Forest Classifier performance was evaluated using the test data set of 1328 samples across the different varieties using the performance evaluation metrics, as shown below in Fig. 16.

Using Random Forest as a classifier, the model was able to classify 232 Banganapalli samples out of 245 samples correctly with an accuracy of 95.9% and 94.4% for Neelam and 96.2% for Rumani varieties. The maximum misclassification or error rate (1- Accuracy) is in the Neelam Category with about 5.6% error. The overall accuracy of the model for the test set of mango variety sample is at 95.5%. It is seen that even in the case of misclassification, the model has been able to distinguish the categories very distinctly, and there is no or minimal confusion between the groups. The results indicate the model behaves well in classifying mangoes according to the different varieties with minimum risk of incorrect classification.6

Similarly, the classification report for the Random Forest Classifier for grading the quality of the mangoes is shown below in Table 9. The sensitivity or the recall value is 95% for

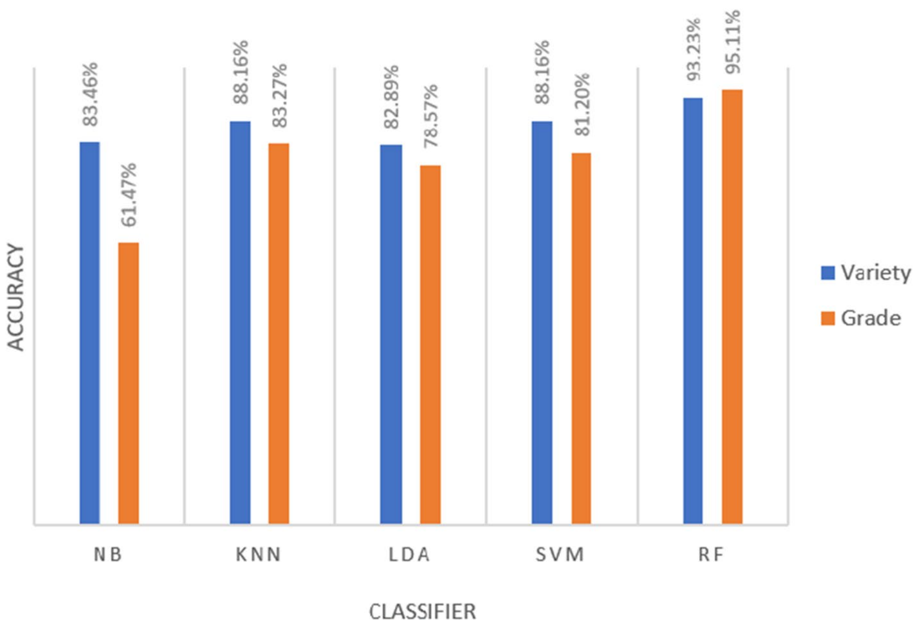


Fig. 15 Comparison of different classifiers for Variety and Quality Grading

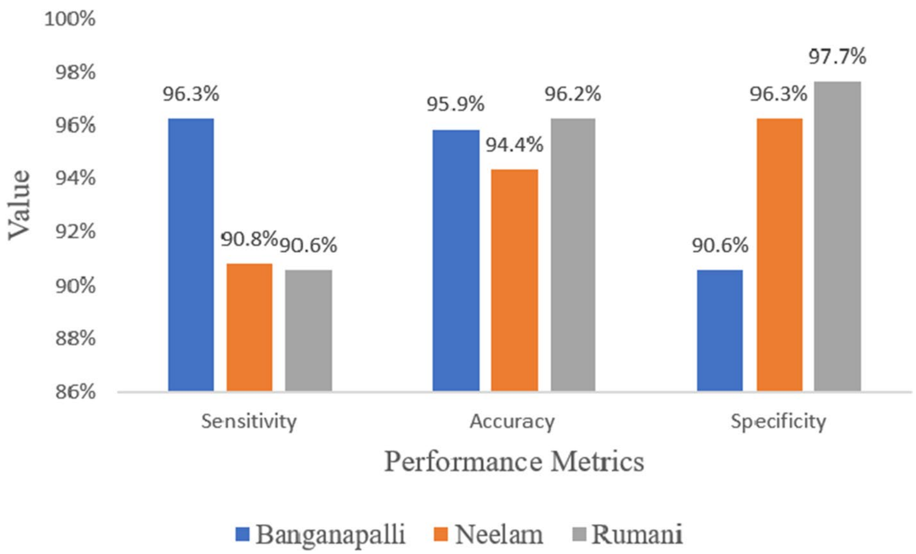


Fig. 16 Performance Evaluation Metrics for Variety Classification

Table 9 Classification report for quality grading

Category	Precision	Recall	f1 – Score	Sensitivity	Accuracy	Specificity	AUC
NotFit	0.96	0.97	0.96	95.50%	97.37%	98.49%	0.9964
Average	0.95	0.95	0.95	95.38%	95.11%	94.85%	0.99
Good	0.93	0.91	0.92	93.06%	97.74%	98.48%	0.9969

NotFit and Average Grades, indicating minimal overlap between the quality grades. The maximum value of specificity of the RF classifier is in category NotFit and Good with a value greater than 98%, indicating very few samples in these categories are misclassified in other categories. The RF classifier accuracy is also above 95%, indicating that most of the samples are correctly classified. In general, the RF classifier has a good performance across all categories and is a fit classifier for correctly grading the quality of mangoes.

The AUC values also show similar performance with values above 0.99, indicating the model is a stable model. The results indicate that the Random Forest classifier is accurate and robust in classifying the various mango grade qualities across the three varieties of mangoes and is a commercially viable quality grade analyzer. The confusion matrix is shown below in Fig. 17.

4.4 Comparison with previous works

In this study, multi-level grading for three varieties of mangoes was done using a combination of CNN, image processing and computer vision methods. Quality grading of mango into NotFit, Average and Good is done based on a combination of multiple feature sets that include ripeness maturity stage, colour, size, shape, GLCM texture, and defects. The first level of grading was done to ascertain the ripening stage of the mango, and then using

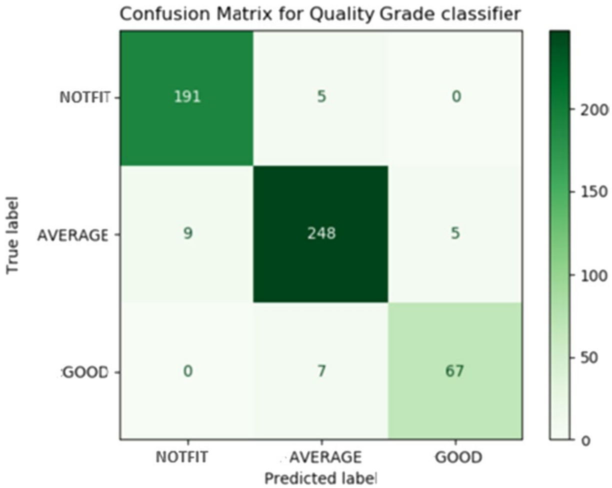


Fig. 17 Confusion matrix for quality grading

the other features like size, colour, texture and defects, the overall quality of the mango is graded into three classes. This type of grading will help the mango stakeholders to decide which mangoes are of export quality and which ones to consume locally. The Notfit variety is the ones that are unfit for consumption and needs to be rejected. So instead of just two classes as good and reject, we have a third class that identifies the mangoes for export and local consumption.

Convolutional Neural Network was used to extract the ripeness maturity stage of mango to improve the overall accuracy of the mango quality grading by using a sizeable labelled dataset created for this study. The CNN was used to identify the in-between ripening stages, Early Ripe and Partial Ripe in addition to the Raw and Ripe stage. This added classification has resulted in the improvement of the overall accuracy of the mango grading. The dataset created for this ripening stage classification is also a reasonable sized labelled dataset bigger than most of the existing works.

This study also compares five different algorithms for variety recognition and quality grade classification. The usage of the Random Forest classifier gave better accuracy in both variety recognition and quality grading. The Random Forest classifier was able to identify the Average and Good Quality mangoes with very high accuracy of 98.1% and 96.1%.

The success of this study motivates extending this solution to other varieties of mangoes and also consider additional attributes like the internal attributes of the mango to improve the overall grading accuracy and quality. The proposed solution was compared with similar works established in the last years, and the results are summarized in Table 10.

5 Conclusion and future direction

The traditional mango quality assessment and grading were done manually and semi-manually by farm experts and warehouses. The grading process was highly inconsistent due to high subjectivity and was labour-intensive, proving to be very costly. The literature survey of the previous works uses mainly a few parameters like either size or colour or size and texture for grading. There is a gap in considering multiple parameters for grading. This study uses a multi-level grading of mangoes based on maturity stage, size, shape, colour,

Table 10 Comparison of the proposed model with other classifiers

Reference	Sample type	No of classes	Accuracy	Comparison feature
Nandi, C. S. and Koley, C. (2014) [13]	5 mango varieties (Kumrapali, Amrapali, Sori, Langra, Himsagar)	4 Ripening Stages (Raw, Semi-matured, Matured, Over-matured)	88%–90%	Size, maturity level grading using Gaussian Mixture model and Fuzzy logic
Supekar, A. D., & Wakode, M. (2020) [21]	Dasheri & Kesar mango	4 grades (Grade 1, Grade2, Grade3, Grade4)	88.88%	Ripeness, size, shape and defect-based grading using Image Processing and grading using manual formula
Salunkhe R. P. and Patil A. A. (2015) [17]	Alphonso mango	4 Ripening Stages (Green stage, Unripen, Ripen and Fully ripen)	90.4% for RGB & 84.2% for HSV	Rule-based classification of ripening stage grading using RGB and HSV colour model
Naik, S. (2019) [18]	Kesar mango	4 grades (Class I, Class II, Class III and Class IV)	83.97%	Shape, size and maturity parameter-based grading using pre-trained CNN model MobileNet and SVM classifier
Proposed Solution	Banganapalli, Neelam, Rumani mango	4 Ripening Stages (Raw, Early Ripe, Partial Ripe, Ripe) 3 Varieties recognition 3 Grade Quality (NotFit, Average and Good)	93.4% 93.23% 95.11%	Improved accuracy with the following features -Ripening stage grading using CNN into four grades -Appearance-based grading of 15 attributes (Size, Shape, Texture, Colour and defects) using Image Processing, Computer vision and RF classifier -Variety Classification -Quality grading

texture and defects. This study aims to develop an intelligent mango grading system to automatically grade the overall mango quality based on external attributes using low-cost affordable portable mobile camera device technology with improved performance.

The proposed mango quality grading system uses a Convolutional Neural Network to compute the maturity ripening stage as a first-level grading. The CNN is used to identify two additional in-between stages of ripening, which helps fine-grain classification of mangoes for grading. The dataset created for this study is also reasonably sized compared to the previous works and improved the overall accuracy of the solution.

The system then uses computer vision, image processing techniques for shape, colour, texture and defect extraction. The combination of maturity ripening stage and shape, colour, texture and defect features are used for further variety classification and final quality grading. The dataset and the features extracted not only help in grading but can also identify the mango variety.

An improvement in the accuracy of the grading algorithms was also essential. The study compares five different classifying algorithms like Naïve Bayes (NB), k-Nearest Neighbor (kNN), Support Vector Machine (SVM), Random Forest (RF) and Linear Discriminant Analysis (LDA) to classify mangoes according to their variety (Banganapalli, Rumani and Neelam) and to grade the quality into NOTFIT, Average Quality and Good Quality. Random Forest was the best-suited algorithm, resulting in an improved classification accuracy of 93.23% for variety recognition and 95.11% for quality grade classification.

The proposed system considers only external factors for quality grading. However, internal properties like Total Soluble Solids have a significant impact on the overall quality. In the future, a system that can combine both internal and external features to grade based on quality will be a more commercially viable product. This study was also limited to only three varieties of mangoes grown abundantly in South India. Since data collection of mangoes across different geographies was a challenge, this study was limited to mangoes grown in farms around Chennai for grading.

In future, the quality grading process can be extended to include internal attributes like Total Soluble Solids, Dry Matter (DM), Firmness for overall quality grading. The solution can also be extended to other varieties of mangoes and other climacteric fruits.

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