Mango Quality Grading using Deep Learning Technique: Perspectives from Agriculture and Food Industry

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ABSTRACT

India is an agrarian country, agriculture business is major source of income. India holds the first rank in mango (Mangifera Indica Linn) production worldwide. The precise grading of the fruit acts extensively in agricultural sector for the commercial development of India. Prior to bring the agricultural products to the market, it is essential to classify and grade them automatically without manual intervention. In this research study, we have designed and implemented deep learning-centered non-destructive mango sorting and grading system. The designed quality assessment scheme comprises of two phases: developing hardware and software. The hardware is built to photograph the RGB and thermal images of mango fruits from all the directions (360°) automatically. From these images, designed software classifies mangoes into three grades according to quality viz. Extra class, Class-I, and Class-II. Mango grading has been done by using parameters such as defects, shape, size and maturity. In the present work, transfer learning based pre-trained SqueezeNet model has been employed to assess grading of mangoes. The test result reveals that classification accuracy of proposed system is 93.33% and 92.27% with the training time of 30.03 and 7.38 minutes for RGB and thermal images respectively and shows four times speed up through thermal imaging.

CCS CONCEPTS

• Computing methodologies ~ Computer vision

KEYWORDS

Maturity; Thermal Imaging; Deep Learning; Transfer Learning

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1 Introduction

Mango is the national fruit in India. It has large demand all around the world for savoury taste, flamboyancy, and high nutritional values. India is the world's largest mango producer country, which yields 54.2% of total world production. It produces almost more than thousand mango varieties in bulk whereas around 30 varieties are developed on marketable scale [1]. According to National Horticulture Board, in 2018-19, India yields 21.822 MMT (million metric tons) of mango fruits and the area under cultivation of it stood to 2.258 MH (million hectares). In 2018-19, India exported nearly 46.51 thousand tons of fresh mangoes which are valued Rs. 406.45 Crore [1, 39]. They are also exported in the processed form, thus opening tremendous opportunities for export. Though the above statistics propose huge prospective for India to come out as the most important fruit exporter, but globally its contribution is nearly 22% only because of its productivity [14]. The reason is that lack of speedy, non-destructive and accurate sorting techniques to quality and guaranteed assurance. To increase profitability and to enhance competitiveness, accurate grading of fruits is essential.

Assessing fruits and vegetables quality endured a phase of active research during last few decades. In the literature, many researchers have implemented sorting and grading system by adopting various computer vision and machine learning methods to varieties of fruits like orange [10], apples [2, 12], tomatoes [3, 11], plum [20], persimmon [26], banana [33], strawberry [34], mangoes [2, 29, 31, 37] etc. using the color, size and defects as main quality parameters and achieved accuracy in the range of 60-100%.

The knowledge of external and internal factors of the fruit is essential for the design of the system like sorting, grading etc.; otherwise it will lead to product loss. In the aforesaid grading system variety of color feature representation methods have been used as external factor of the fruit. Color representation comprises RGB [34], color histogram [12], CIE Lab [27], thresholding [32], surface texture [5, 15], statistical analysis [3, 4].

An approach to determine the internal quality factors without damaging the fruit is stated as non-destructive approach. These techniques mostly utilize several imaging modalities such as hyperspectral imaging [12], multi-spectral imaging [23], infra-red imaging [35], and thermal imaging [7, 8, 30] to enhance the accuracy of the analysis in general. Further, Bulanon et al. [9] has investigated the applicability of thermal imaging in the recognition of fruits. The authors [8, 18, 19, 23] have applied thermal imaging for detection of bruises and results show that it has more discerning influence than RGB images. Some researchers proved that thermal imaging is beneficial in fruit maturity detection [28, 30].

Globally, deep learning (DL) has emerged as a new perspective in the research arena. It is also a popular practice in image classification and recognition tasks. The developments in deep learning research have attracted the agriculture industry for applications like fruits and vegetables quality detection, and classification [17, 29, 38]. Also, it has been proposed in the food industry to examine food spectral images [36].

As per the aforesaid literature, many research papers have been published on deep learning and it's various applications based on RGB imaging, but very few papers have been published relating spectral sensing along with deep learning.

Therefore, we have attempted to design a system using non-destructive thermal imaging by deep learning technique which predicts the maturity levels of mango for evaluating the quality with increased accuracy. The successful execution of such a system will help to reduce manual inspection costs, improve the product quality and increase export efficiency. Also, thermal imaging can be useful to find the maturity of mango like Langra whose external skin color remains the same till its senescence stage. Langra mango retains its green color after it gets ripe, so it is difficult to find a maturity index using external skin color.

2 Materials and Methods

The determination of fruit grading quality is an important factor in the agricultural segment. This is because maturity is prime index to identify the quality and largely related to business of the produce. Mostly manual approach has been used in the fruit grading which advances problems in maintaining uniformity, time-consuming, and tiredness by the human operators. In proposed study, we design and implement deep learning-centered non-destructive mango grading system. The methodology comprises of below mentioned steps:

1. Collecting mango fruits for the preparation of samples to acquire the RGB and thermal images.
2. Measuring the weight of the fruits using digital weighting scale.
3. Designing the automatic image capturing system based on normal and thermal camera.
4. Assessing fruit grading quality based on bruise, size and maturity parameters.

2.1 Sample Collection and Preparation

Around 10 kg of mango fruits of the 'Kesar' variety has been collected from the farm of three different locations i.e. Valsad, Junagadh and Ahmedabad districts of Gujarat, India at the end of the month of May, 2019 for this research. The peel color of 'Kesar' is slightly mottled yellow with a green shade [1, 14]. Earlier research has noted great variation in the peel color of the cultivar 'Kesar' during maturity. This factor has raised the curiosity of many researchers to examine such cultivar for these features [28]. These fruits were examined for any external damages and spots. Then, they were washed and dried for 1 hour. Each fruit was wrapped with paper and labeled for identification purpose. They were stored in the container under natural atmospheric conditions (temperature of 29°C±2°C and relative humidity of 72.4%±3%) for regular analysis. For the non-destructive assessment of fruit grade quality, 41 mango fruits have been used. The sample weight of 'Kesar' fruits ranges from 145 gm to 363 gm. Every day after 24 hr interval, for each mango fruit the weight has been measured using digital weighing scale and images have been captured till the decay of fruit.

In India, grading of the mango fruit has been done through AGMARK standards with 3 classes: Extra class, Class_I, Class_II. For mango grading purpose, samples have been classified into bruising parameter viz. damaged and healthy, size parameter viz. big, medium and small and maturity parameter viz. unripe, partially ripe and ripe. Table 1 specifies the criteria for all the above parameters where 'days' in maturity classes depicts number of days have been passed after harvesting and grading of the mangoes based on these parameters are represented in Table 2.

Table 1: Size parameter and Maturity parameter

Size_Classes	Size in grams
Big	275 and above
Medium	225-275
Small	< 225

Maturity_Classes	Days
Unripe	1-8
Partially_Ripe	9-14
Ripe	15-19

Table 2: Parameters for grading of mangoes

Grade_Class	Size_Class	Maturity_Class
Extra_Class	Big	Unripe, Partially Ripe
	Medium	Unripe
Class_I	Big	Ripe
	Medium	Partially Ripe, Ripe
	Small	Unripe
Class_II	Small	Partially Ripe, Ripe

2.2 Image Acquisition

Acquiring an image is a crucial step for obtaining high-quality images and developing an automatic grading system for fruits. The images have been acquired automatically by the system as proposed by Bhole et al. [5] and saved on a computer. Every day, we have taken RGB and Thermal images of almost 41 mangoes. The images have been captured with a resolution of 2322 x 4128 and 720 x 1280 pixels using smart phone normal camera and the SEEK Thermal camera respectively. The images were photographed between 2 P.M. to 5 P.M. This procedure was repeated for around 18-19 days. The background, time to capture photographs, lighting conditions, and distance between camera and fruit were retained fixed during these days. Nearly 10000 images of dataset have been created for the study. Figure 1 exhibits sample RGB and Thermal images of size, maturity and grading parameters.

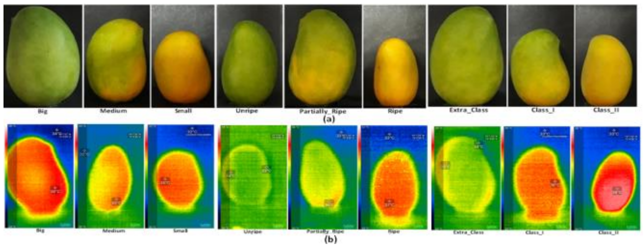

Figure 1: Sample mango images for size, maturity and grading parameter of (a) RGB (b) Thermal dataset

2.3 Mango Fruit Grading System

The grading of the mango fruit has been determined by classifying them in accordance with their quality. The steps for the development of mango fruit grading classification are explained below and exhibited in Figure 2.

1. Image Dataset: The RGB and thermal datasets have been created from the acquired images of mangoes for each parameter like size, maturity, and grading where 500 images have been utilized in every class of parameter.
2. Image augmentation (Pre-processing): The captured both RGB (2322 x 4128 x 3) and Thermal (720 x 1280 x 3) images are down-sampled into (227 x 227 x 3) as the size of the SqueezeNet model is (227 x 227 x 3).
3. Split dataset with 75: 25 proportions for training and test set of images respectively.
4. Train the training dataset with pre-trained CNN through SqueezeNet model via transfer learning.
5. Classification: Fit the model and verify the system through the test set. For classification of each parameter (size and maturity) repeat step 2 to step 4.
6. Predict labels and its probabilities for the new set of images.

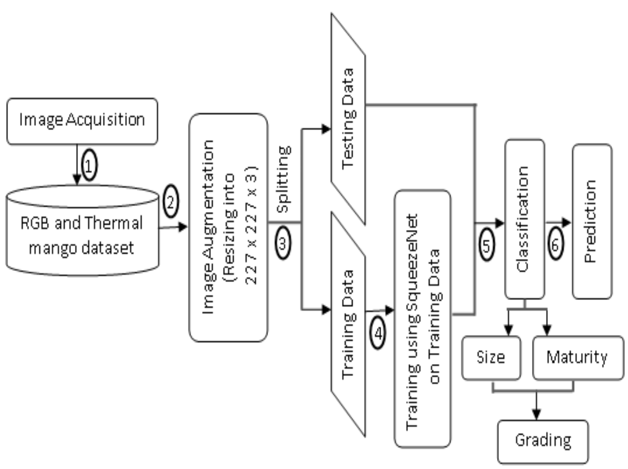

Figure 2: Proposed mango fruit grading classification

2.4 Proposed CNN based SqueezeNet Structure

The proposed system is based on SqueezeNet [15] deep CNN and has been selected for this study because of its smaller size (4.6 MB) and requires only 1.24 million parameters to train the network.

2.4.1 SqueezeNet Model Architecture. In the current study, we propose CNN based SqueezeNet model to classify RGB and thermal fruit images for prediction of size, maturity, and grade of 'Kesar' mango fruits. The SqueezeNet incorporates total 68 layers; which is 18 layers deep coupled with 72 connections [6]. The proposed fine-tuned CNN based SqueezeNet framework is demonstrated in Figure 3 which initiates with convolution layer (conv1), proceed with eight fire modules i.e. fire2-fire9 and lastly finished with convolution layer (new_conv) which is renamed in this work for conv10 (last convolutional layer). In fire modules the number of filters has been increased progressively from sixty four within the early block (start of the network) till 512 within the final block (end of the network).

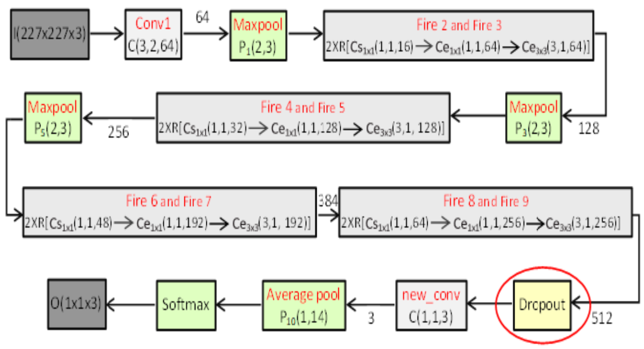

Figure 3: Proposed fine-tuned SqueezeNet framework

These fire modules which are building blocks of our fine-tuned net comprises a sequence of filter banks with kernels 1x1 and 3x3 for squeeze convolution layer (s_{1x1}) including two expanded convolution layers (e_{1x1} and e_{3x3}). The max-pooling (taking maximum value from the input) is executed after the conv1, fire3, fire5, and average pooling (taking the average value from input) after new_conv (conv10) layers by shifting 3x3 mask to 2 pixels at a time i.e. stride = 2 to minimize the quantity of parameters. Here, ReLU function was activated after each and every convolution layer to speed up the training process which is given in equation 1 because of which all the negative values were set to 0 [21].

$$f(y) = \begin{cases} y, y \geq 0 \\ 0, y < 0 \end{cases} \tag{1}$$

To decrease the chances of over-fitting and improve the network performance, dropout using a probability of 0.5 has been utilized after the fire9 module. If drop out has been added after convolution layer instead of fire9, the performance gets degraded because in the output layer, we are using Convolution2DLayer instead of fully connected layer. At the end, the softmax activation function for multi-class classification is given in equation 2, has been adopted in output (Convolution2D Layer) layer to predict the score of model for 3 classes of each parameter viz. size (Big, medium, small), maturity

(Unripe, Partially_ripe, Ripe) and grade (Extra_Class, Class_I, Class_II) to define quality of mango fruits.

$$P(c_n|x,\theta) = \frac{P(x,\theta|c_n)P(c_n)}{\sum_{i=1}^{j} P(x,\theta|c_i)P(c_i)} \quad (2)$$

where, $P(x, \theta | c_n)$ is the conditional probability of input given class n and $P(c_n)$ is class prior probability. Also, $0 \le P(x, \theta | c_n) \le 1$ and $\sum_{i=1}^{j} P(x,\theta|c_i) = 1$.

In Figure 3, the notations in the blocks are defined as

- I(227x227x3): augmented input image with width and height as 227x227 along with 3 channels as we are using color images.
- P(s, f): pooling layer where s indicates stride and filter size fxf.
- C(f, s, n): convolution layer where s indicates stride, f is the filter size and n is number of filters or features.

In fire modules,

- C_{sfxf} and C_{efxf} represent squeeze convolution layer and expanded convolution layer with filter size fxf.
- 2xR[.]: R signifies repeated block [.] and 2xR means block repeated twice.
- O(1x1x3): output that represents scores for each the 3 classes of the every parameter.

The proposed net has been trained by Adam optimizer [21] through cost function as categorical cross-entropy loss function (CCEL) and defined in equation 6 for both RGB and Thermal dataset. Adam is the adaptive moment estimation (whose default learning rate = 0.001) which evaluates gradients first (mean) and second (uncentered variance) moments to adjust the learning rate of every weight of the network on existing mini-batch which is specified in equation 3 and 4 respectively. The weight has been updated using equation 5. The optimum learning rate mainly influenced by the dataset used. Here, a transfer learning approach has been used for fine tuning the pre-trained SqueezeNet network. So, the network weights need to be changed less aggressively; for which we have to select the learning rate lesser than the default i.e 0.001. We have set some training options along with hyper-parameter as learning rate = 0.0001, mini batch_size = 32 and 10 epochs with total 350 iterations (35 iterations per epoch) as well as mini batch_size = 16 and 5 epochs with total 350 iterations (70 iterations per epoch). The weights for these hyper-parameters have been finalized by executing the experiments several times.

$$mean_t = GDF_1\, mean_t + (1 - GDF_1)\, g_t \quad (3)$$

$$variance_t = SGDF_2\, variance_t + (1 - SGDF_2)\, g_t^2 \quad (4)$$

$$w_t = w_{t-1} - n\frac{mean_t}{\sqrt{variance_t} + \varepsilon} \quad (5)$$

$$CCEL = -\sum_j^C t_j \log(s_j) \quad (6)$$

where in the above equations 3,4,5, and 6, $mean_t$ and $variance_t$ depict moving averages for the gradients (g_t and g_t^2) respectively. GDF_1 and $SGDF_2$ have been chosen to be Gradient_Decay_Factor and Squared_Gradient_Decay_Factor having default parameter values as 0.9 and 0.999 respectively. w_t and n represents the weights and batch size respectively. t_j and s_j are actual and predicted scores for each class j in C.

The feature extraction has been performed by convolution and pooling layers. The early convolutional layers like conv1, fire2 module detect low-level features like edges, shapes while convolutional layers at the end of the network like new_conv, fire9 module extract high dimensional features which provides less information regarding the image but more related to the class of the image which is less visibly recognizable. The squeeze and expand layer in fire module keep the equal feature map size, however the earlier downsize the depth to a small number (fire2-squeeze has 16 features), then later increase it (fire2-expand has 64 features). The depth has increased from 64 to 512 whereas reducing feature map size from 227x227 to 14x14 for getting high-level abstract.

3 Results and Discussion

The usage of any deeper network is dependent on available hardware resources. We have tried various pre-trained networks and executed the experiments numerous times for evaluating their performance with respect to accuracy and training time and finally chosen fine-tuned pre-trained SqueezeNet model due to its smaller size which is suitable for limited hardware resources. The training has been performed on GPU (Nvidia GeForce 730M with 384 CUDA cores) because of its high performing capability.

3.1 Experimental Results

In all experiments, adaptive moment estimation (Adam) has been chosen for optimization as it works well in our case.

3.1.1 Experimentations on RGB Dataset. In the current section, the results of all RGB datasets for size, maturity, and grade parameters have been discussed. Here, for fitting the network on training data, a meager value of 0.0001 has been used for the learning rate over 5 epochs with total 350 iterations (70 iterations per epoch) coupled with mini batch size of 16. The confusion matrix in Figure 4 exhibits behavior of the model over test dataset of size, maturity and grade parameter respectively. Here, row summary is stated as Recall and False Positive Rate (FPR) and column summary as Precision and False Discovery Rate (FDR) for true and predicted class respectively. The entire training process for grade datasets across RGB has been depicted in Figure 5. The four sample test images along with predicted labels and its probability of bearing those labels has been displayed in Figure 6 for the maturity and grade parameters.

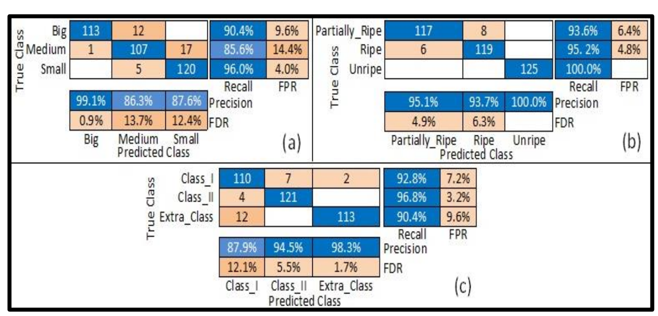

Figure 4: Confusion matrix for RGB dataset of parameters (a) Size (b) Maturity (c) Grading

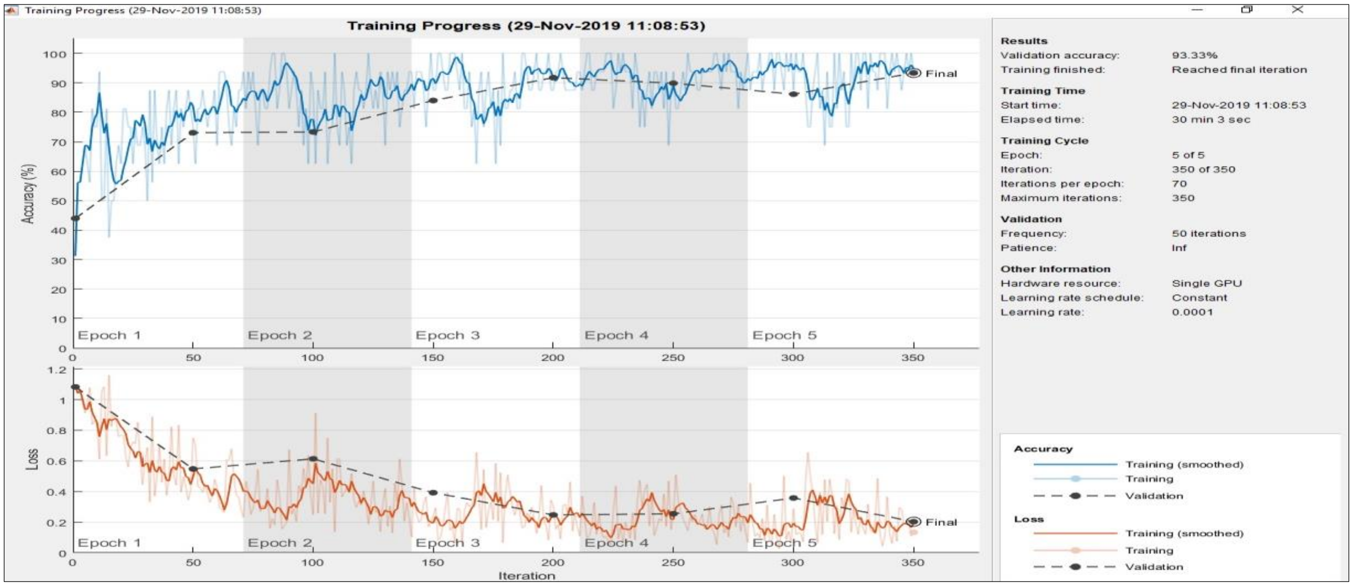

Figure 5: Training process for grading of RGB dataset

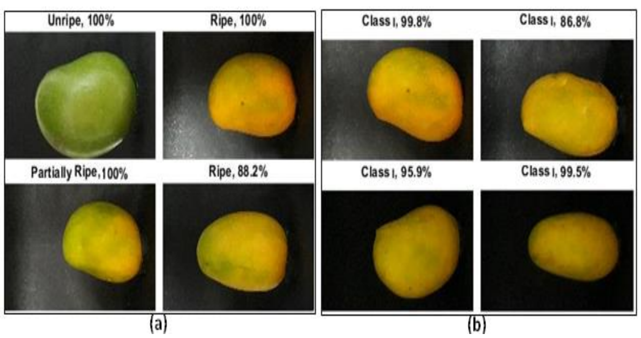

Figure 6: Sample predicted images and its probability of RGB dataset for (a) Maturity (b) Grading parameter

3.1.2 Experimentations on Thermal Dataset. In the present section, the results of all thermal datasets for size, maturity, and grade parameters have been discussed. Here, the model was trained with learning rate = 0.0001 along with mini batch of 32 and 10 epochs with total 350 iterations (35 iterations per epoch). The overall training process for grade thermal datasets has been illustrated in Figure 7. The confusion matrix in Figure 8 demonstrates the efficiency of the network on test image dataset. The samples of four test images with their predicted labels and its probability of holding those labels have been displayed in Figure 9 for the parameters of maturity and grade respectively.

Table 3 summarizes the classification accuracy, time required for training the network and speed up for all the RGB and thermal datasets and elucidated in Figure 10. It is crystal clear from the study of the table that thermal imaging based approach achieves 4X speedup in training time compared to RGB while still maintaining the baseline accuracy level of RGB images.

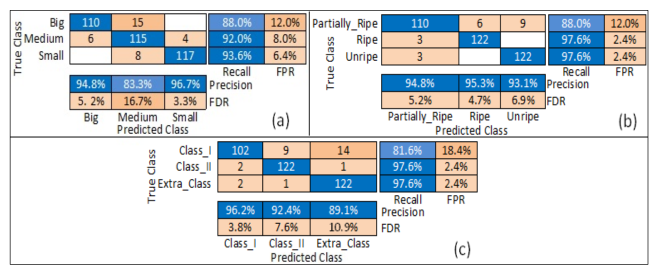

Figure 8: Confusion matrix for Thermal dataset of parameters (a) Size (b) Maturity (c) Grading

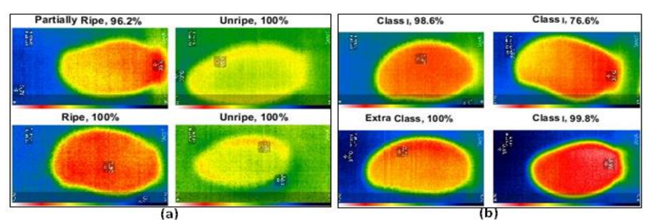

Figure 9: Sample predicted images and its probability of Thermal dataset for (a) Maturity (b) Grading parameter

Table 3: Mango quality evaluation results(RGB & Thermal)

Sr. No	Dataset	Batch	Epoch	Accuracy (%)	Time (minutes)	Speed up
1	RGB_Size	16	5	90.67	30.31	
2	Thermal_Size	32	10	91.2	7.3	4.15x
3	RGB_Maturity	16	5	96.27	30.55	
4	Thermal_Maturity	32	10	94.4	7.21	4.1x
5	RGB_Grade	16	5	93.33	30.03	
6	Thermal_Grade	32	10	92.27	7.38	4x

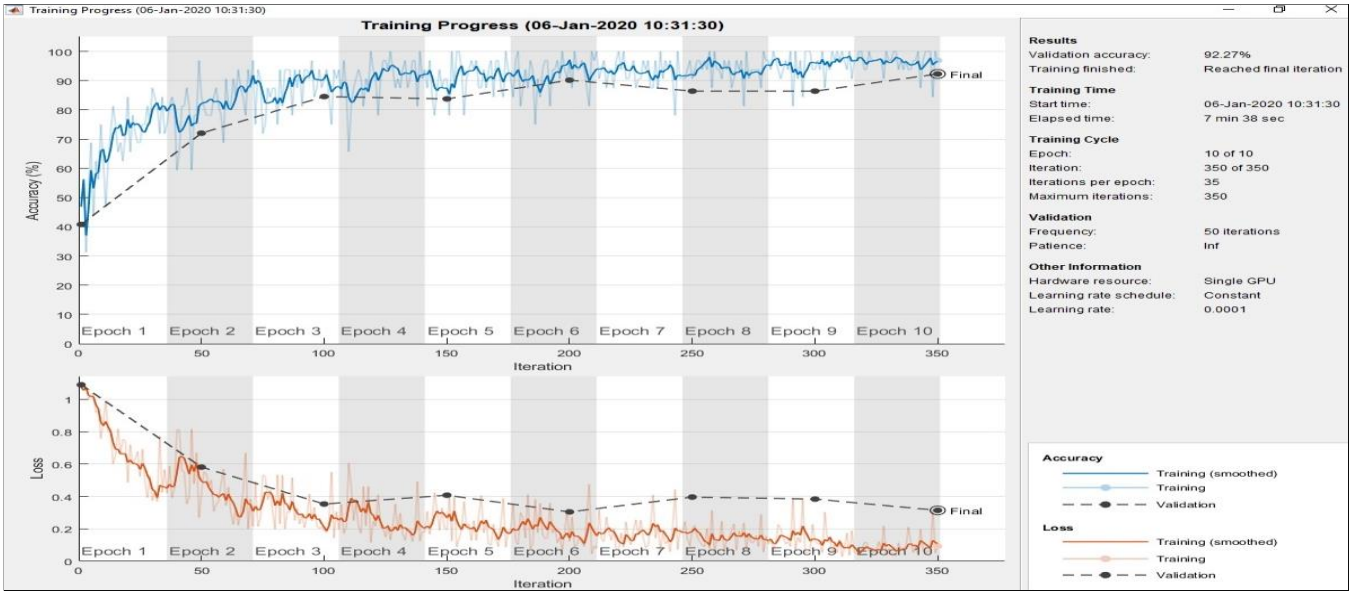

Figure 7: Training process for grading of Thermal dataset

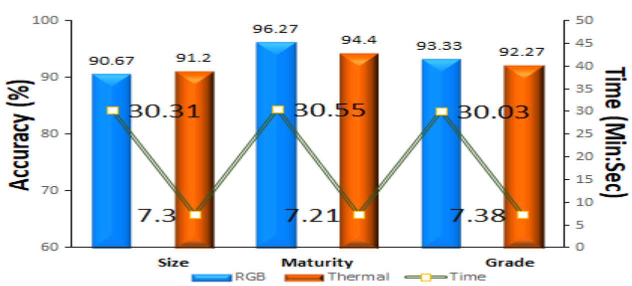

Figure 10: Evaluation metric of RGB and Thermal dataset

3.1.3 Comparative Work. We have compared the proposed work with the other researchers, for thermal [28] and RGB [29] dataset. For the RGB dataset, author [29] achieved the accuracies for size, maturity and grading – 72.46%, 82.04% and 83.97% respectively using pre-trained MobileNet model for extracting the features and SVM for classification. In Table 4, analysis for RGB dataset results have been statistically summarized which shows improvement in the results of the proposed work. In [28], the grading has been performed based on size and maturity parameters using the L*a*b color model and fuzzy classifier. The accuracies recorded by the researcher were 92%, 86% and 89% for size, maturity and overall grading respectively which is considerably good in the present research work with a transfer learning approach for thermal dataset illustrated in Table 5.

Table 4: Comparative work of RGB dataset with [29]

RGB Dataset	Accuracy (%)			Techniques Used
	Size	Maturity	Grading	
[29]	72.46	82. 04	83.97	MobileNet + SVM
Proposed	90.67	96. 27	93.33	Fine-tuned SqueezeNet

Table 5: Comparative work of RGB dataset with [28]

Thermal Dataset	Accuracy (%)			Techniques Used
	Size	Maturity	Grading	
[28]	92	86	89	Image Processing + Fuzzy Classifier
Proposed	91.2	94.4	92.27	Fine-tuned SqueezeNet

4 Conclusion

The factors like bruises, color, appearance etc. affect the quality of the fruits and also influence the consumers. This research focuses on non-destructive techniques that determine the maturity levels of the mango for evaluating the quality with increased accuracy. So, we have proposed an automatic mango fruit grading system using non-destructive techniques like thermal imaging and transfer learning with pre-trained SqueezeNet model which is a new era at present.

The proposed methodology has been evaluated with two datasets; the first one is RGB and second is the thermal. On RGB dataset, the size, maturity and grade parameters witnessed accuracies of 90.67%, 96.27% and 93.33%, respectively with the training time of 30.31, 30.55, and 30.03 minutes. Along with the training time 7.3, 7.21, and 7.38 minutes, the classification accuracy of 91.2%, 94.4% and 92.25% were noticed for thermal dataset for the size, maturity and grade classes, respectively. So, it can be observed from the results that thermal imaging is able to reduce training time by factor of 4X while meeting the accuracy of RGB images. So, this experimentation helps the agriculture industries to update their business processes and also leverage IT education. From a futuristic perspective, we can raise the bar of present work with different cultivars of mangoes as well as fruits.

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