# Fruit-CNN: An Efficient Deep learning-based Fruit Classification and Quality Assessment for Precision Agriculture

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***Abstract*— Diseases of fruits and assessment of their quality are one of the key challenges in the farming sector and their automated recognition is very critical to save time and avoid financial loss. The process of manually looking at and identifying the fruit type in crops can be a cumbersome task, the time from which could be put to better use. In this paper, a novel deep learning-based architecture Fruit-CNN has been proposed to identify the type of fruit and their quality assessment of real-world images in multiple visual variations which achieves a test accuracy of 99.6%. The proposed architecture takes minimal time to train the large dataset and test fruit images in comparison with state-of-the-art deep learning models which proves its wide applicability in precision agriculture. More images belonging to various classes can also be trained with fewer parameters which result in fast training of models and less processing time.**

***Keywords*— Deep Learning; Fruits Recognition; Object Identification; Quality assessment; Real-time***

## I. Introduction

Agriculture is vital to the overall sustainability of a country's economic development. In addition to producing food and raw resources, agriculture provides employment opportunities for a large number of people. Agriculture is the primary source of income for the majority of a country's people. Changing demand as a result of rising incomes, globalisation, and more health awareness has an impact on production. In the future, there will be more demand for fruits, vegetables, dairy products, seafood, and meat [1]. A major constraint of framing in developing countries like India is the underutilization of automation and mechanized processes. About 58% of the total Indian population is primarily dependent on agriculture for their livelihood. India has enormous revenue potential in food processing sector which is destined for massive expansion global food trade. The grocery and food market in India is the world's sixth largest, with retail representing 70% of sales revenue. The Indian food processing industry contributes for 32% of overall food market of the country [2].

India's diverse climate offers access to a wide range of fresh fruits and vegetables [3]. After China, India is second-largest producer of fruits and vegetables globally. Grapes, Pomegranates, Mangoes, Bananas, Oranges account for the largest portions of fruits exported from the country. Labour is the largest element of cost in fruit and nut production. For these reasons it becomes essential to come up with a way to convert the time taken to manually categorize and harvest all the fruits into other crop processes, thus increasing total production. Defective fruits are the leading cause of financial crises in the agricultural farming business around the world. It has an impact on the standards and quality of fruits [4]. Quality monitoring is a time-consuming and highly specialised post-harvest process.

For manually harvested citrus orchards, low harvesting efficiency is a significant issue. Time spent on non-picking tasks can account for more than half of overall working time in some situations [5]. Robotics or mechanized arms, as well as the torsion technique of detaching, are regarded suitable for citrus fruits intended for the fresh fruit market, because the calyx is not eliminated [6]. To facilitate the mechanical harvesting to its fullest extent a detection system is needed which can allow us to identify the different categories of fruits. A relatively unexploited idea is in the form of using a deep learning and artificial intelligence algorithm to not only detect the species of fruit but also whether the fruit is ripe or not. This can prove to be lucrative as it could give a status on the growth of crops and the individual number of ripe and unripe fruits, useful information for deciding whether it is time to harvest or not. For higher-level agriculture operations like yield monitoring and robotic harvest, a precise and reliable image-based fruit detection method is essential.

The main contribution of the proposed work is to develop a novel deep learning-based Fruit-CNN model for fruit recognition and their quality assessment. Images of six different fruits in 12 distinct categories in real-world situations have been considered in the collected dataset based on their quality. An extensive dataset of 12000 images in different categories has been taken to train proposed convolutional neural network (CNN) architecture for multiple epochs and testing the trained deep learning model. With complicated background conditions, images show considerable inter-class and intra-class variation. For training and analysing the framework, the gathered dataset is split into three subsets: training, validation, and testing. The proposed deep learning-based method outperforms other state-of-the-art models and has achieved an accuracy of 99.6% accuracy on test set of unseen images. The proposed fruit recognition and quality assessment model has demonstrated promising outcomes in real-time and can be connected with camera-based systems for analysing fruit quality. The proposed architecture of Fruit-CNN has fewer parameters which make it more efficient to train a large number of images in less amount of training time and subsequently, the time taken to process the real-world images is also less, which makes it better suitable in precision agriculture.

The remainder of the paper is organised in the following manner. Previous works with different methodologies in fruit recognition have been discussed in the section II. The data collection and deep neural network design are discussed in detail in Section III. The outcomes of the experiments were discussed in Section IV. The proposed work is concluded in Section V.

## II. Related Works

Many automated techniques have been developed to detect the quality of fruit for minimising human efforts, cutting the cost of production, and saving production time [7]. As a result, automatic quality identification of fruits is a vital step in the harvesting that assists to save manpower and time. Using image processing and machine-learning approaches, many systems have been developed to detect and classify the quality of fruits. A system using artificial intelligence-based approaches has been developed to speed up the fruit sorting process. The automated harvesting systems will not be misunderstood to pick the harvest pre-maturely as long as it detects a fruit there, it will instead also be able to assess what condition the item is in and then process the next action. [8]. In recent work, early and late fusion methods were investigated in the development of the multi-model Faster R-CNN method for fruit detection utilising RGB and near-infrared images [8]. In another work, M. Afonso et al. used Intel RealSense cameras to demonstrate a Mask-RCNN-based deep learning approach for tomato fruit detection and their counting in production greenhouse [9]. With practical implementation of detection mechanism, a Faster R-CNN based object identification framework was applied for fruit detection in orchards, including apples, almonds, and mangoes [10]. A model with ResNet-101 as the backbone which performed semantic segmentation on apple and apple branches obtained an accuracy of 77.2% [11]. Other methods either use basic computer vision techniques, like colour-based segmentation, or sensors such as hyperspectral, 3D or LWIR etc.

Chemometrics pre-processing of spectral data is generally used to improve predictive outcomes of fresh fruit quality assessment of near-infrared models. Various pre-processing procedures are utilised to eliminate scattering effects and reduction of scattering information degrades the performance of the predictive model because scattering and absorption qualities are very important to describe the physicochemical state of the fruit [12]. The enhanced performance of the 1-D deep learning models has been achieved in raw data without pre-processing of a dataset of NIR spectra. External impacts in multi-batch near-infrared experimentations linked to fruit quality assessment have also been rectified using the FRUITNIR-GUI graphical user interface [13]. Time-temperature indicators are low-cost techniques for predicting food quality while it is being stored. The activation energy has been used to build correlations between colour changing qualities and fruit quality indicators such as antioxidant capacity, Vitamin C, soluble solids, titratable acidity, and weight loss [14]. The Near-infrared hyperspectral imaging spectral calibration model for the quick assessment of pomelo fruit quality has also been optimised using several chemometric approaches [15]. The predictive performance was improved by using deep learning with partial least squares and a Gaussian radial basis function.

Heat detected by thermal infrared imaging from the fruit's surface have non-uniform temperature difference in faulty tissues of the fruit pulp. By analysing the IR image and RGB images with three-level validation techniques, a thermal IR imaging-based method was presented to recognise and evaluate internal defects in pome fruit [16]. Hardness is another essential quality parameter that influences fruit product quality. A quick non-destructive detection approach based on visible and near infrared diffuse reflectance spectroscopy with the sample set partitioning using joint x–y distances, random forest, and partial least squares were suggested to test the feasibility of detecting the hardness of figs without damaging them [17].

A computer vision-based technique for detecting exterior defects on tomatoes was created utilising deep learning without feature engineering, and fine-tuning surpassed feature extraction in detecting external defects. Deep learning is widely used in the detection of disease in the agricultural domain with proven efficiency and multiple drone-based techniques were also suggested [18]. ResNet50, which had all of its layers fine-tuned, was found to be the best model, with an average precision of 94.6% on the test set [19]. For mono and bi-coloured apples, an automated fruit grading model has been built that includes segmentation, feature extraction, and classification algorithms. Four different datasets have been used and obtained accuracy in the range of 87.91% and 95.21% [20].

The main caveat with these precedents is the real-life deployment of these systems and the enormous training time, along with the limitation presented by having only a few selected or in many cases a singular class. This means that there is a requirement of a framework that doesn't have training time as a constraint and can be realistically implemented as a real-time application.

## III. Materials and Proposed Methodology

### A. Dataset Description

The dataset used for the proposed work was FruitsGB, having 12,000 image of six fruits in 12 different categories and each class making up 1,000 images [21]. The data set includes the top six Indian fruits that are traded or highly consumed, as well as labelling for fruit classification and quality. The images of fruits were captured with the mobile phone's rear camera in high resolution quality which were later down-sampled to a size of 256×256 pixels. Diverse lighting conditions in the lab or outside in the sunlight with various background conditions were also used to obtain images. The data set contains 12 classes of six fruits namely Apple, Banana, Guava, Lime, Orange, and Pomegranate with both good and bad quality labels. The images were taken from various perspectives, with various surroundings, and in various lighting scenarios.

For the task of training deep learning model for detection of various types of fruits 11,000 were used and the remaining images were grouped into two batches of 500, one to be used as validation set and the other as the final test set in order to provide a satisfactory evaluation of the model. Fig. 1 shows the examples images of each classes of the dataset. Dataset has huge inter class and intra class variation in terms of position of the fruit, lighting conditions and backgrounds which make it more challenging.


Fig. 1. Visualization of some images of Dataset

## *B. Proposed Methodology*

CNN models are very efficient and have been shown to be useful in the recognition and categorization of objects. A CNN model's usual design includes one or more convolution layers that are alternately linked with pooling layers. The flattened or fully-connected layer is then attached, accompanied by classification functions. Convolution is an important concept, and the convolutional layer is a key component of a CNN model where the convolution of the reference signal mathematically yields the third signal. A small kernel slides over given fruit image across all points inside the perimeter of the image, resulting in a single convolved value that provides a 2D feature map for each position of the kernel. The architecture of the proposed Fruit-CNN is shown in Fig. 2.

The proposed methodology makes use of deep learning and the proposed Fruit-CNN architecture composed of multiple layers having different functionalities, stacked to form a composite network for classification of images. Initially, the images in the dataset to be used were resized to dimensions 224×224×3, after which the data encoded is normalized and one-hot vectors for each of the images were computed. This is then fed as input into the model, which begins with a single convolutional layer with 3×3 sized 32 filters with a stride of 2, followed by a ReLU activation function. A ReLU activation is used in the layers of a deep neural network as it allows for the computation of a complex non-linearity. The ReLU function can be represented as in (1).

$$y=\max(0,x) \tag{1}$$

The graph mapped out by this equation has a slope of 1, meaning that learning is efficient and is not compromised like in the *tanh* and *sigmoid* activations for which the learning becomes almost zero for very high or low numbers. Batch normalization is then performed to combat the obstacle posed by vanishing and exploding gradients, an added advantage is that the data is better centred and normalized-having the mean activation close to 0, providing easier computations. A max-pooling layer is then applied to condense the size of the inputs into the next layer. In a max pool layer, the only maximum of the inputs is taken from a kernel fitted over of the inputs of the entered size. This max-pooling layer has a kernel size of 3×3 and a stride of 2. This is followed by two convolutional layers of 64 filters, with kernel size 3×3, ReLU activation function and the former having a stride of 2. Another set of batch normalization and max-pooling is next with the same parameters as the last time except a kernel size of 2×2. The final block has a convolutional layer with 124 filters and the continuing trend of kernel size persists as well as batch normalization and the ReLU function. Flattening of the data into a single channel occurs, after which two dense layers of 1028 and 256 hidden units were added, respectively with ReLU activation function. The last layer of the architecture is unique in the sense that it has a softmax activation function unlike other layers of the architecture, which is used for multi-class classification problems, hence the number of units in this dense layer is also equal to the number of categorised outcomes for a given fruit image i.e. 12. The detailed information of the parameters in different layers is given in Table I. For each input fruit image, output images and feature visualizations are exhibited in Fig. 3 from each convolutional, pooling, and batch normalization layer of a Fruit-CNN model.

The proposed deep learning architecture of Fruit-CNN predicts the given images of fruits in the category with the most similar extracted characteristics after a layer by layer processing. Batch normalization has been used in the

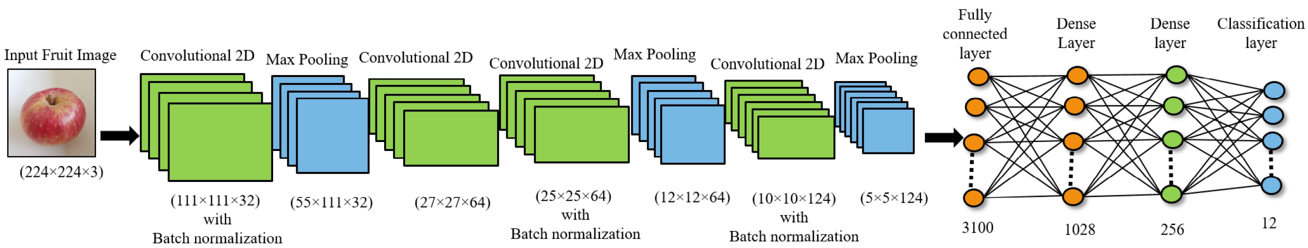



Fig. 2. Proposed architecture of the Fruit-CNN

TABLE I. MODEL ARCHITECTURE LAYERS WITH RESPECTIVE PARAMETERS

| No. | Layers | Filters | Kernel/ Pool Size | Stride | Activation Function | Output Shape | Number of Parameters |
|---|---|---|---|---|---|---|---|
| | Input Image | | | | | 224, 224, 3 | |
| 1 | 2D Convolutional | 32 | 3×3 | 2 | ReLU | 111, 111, 32 | 896 |
| 2 | Batch Normalisation | | | | | 111, 111, 32 | 128 |
| 3 | Max-Pooling | | 3×3 | 2 | | 55, 55, 32 | 0 |
| 4 | 2D Convolutional | 64 | 3×3 | 2 | ReLU | 27, 27, 64 | 18496 |
| 5 | 2D Convolutional | 128 | 3×3 | 2 | ReLU | 25, 25, 64 | 36928 |
| 6 | Batch Normalisation | | | | | 25, 25, 64 | 256 |
| 7 | Max-Pooling | | 2×2 | 2 | | 12, 12, 64 | 0 |
| 8 | 2D Convolutional | 124 | 3×3 | 2 | ReLU | 10, 10, 124 | 71548 |
| 9 | Batch Normalisation | | | | | 10, 10, 124 | 496 |
| 10 | Max-Pooling | | 2×2 | 2 | | 5,5,124 | 0 |
| 11 | Fully-connected Layer | | | | | 3100 | 0 |
| 12 | Dense Layer | | | | ReLU | 1028 | 3187828 |
| 13 | Dense Layer | | | | ReLU | 256 | 263424 |
| 14 | Classification Layer | | | | Softmax | 12 | 3084 |
| | **Trainable parameters** | | | | | | 3,583,084 |
| | **Non- Trainable Parameters** | | | | | | 440 |
| | **Total Parameters** | | | | | | 3,582,644 |

proposed model to prevent the occurrence of overfitting. When the quality of the fruit deteriorates, different visual features are generated, and categorization is done using a deep learning algorithm to recognize different patterns. To distinguish from other category fruits photos, the deep learning model attempts to learn various patterns produced owing to their shape and degradation of quality.

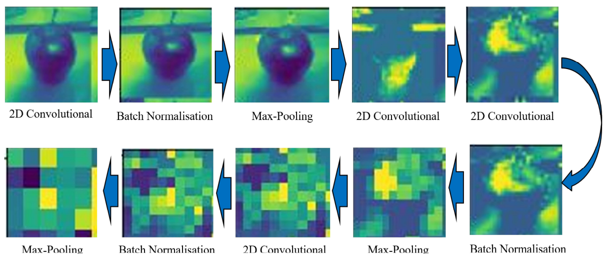



Fig. 3. Feature visualization in different layers of Fruit-CNN model

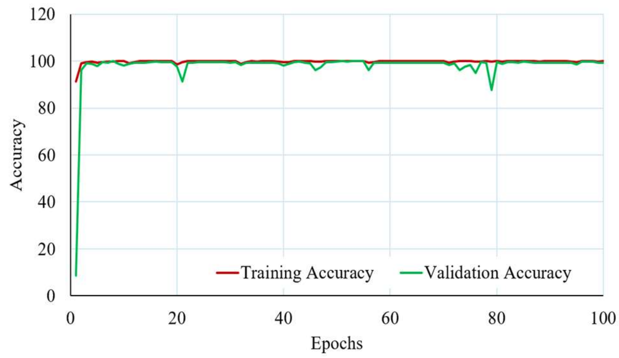
## IV. EXPERIMENTAL RESULTS

The hardware specifications of the training system include Windows 10 operating system with 64 bit Intel Xenon Gold 5218 CPU, the processing speed of 2.30GHz, installed RAM of 64 GB, NVIDIA Quadro P600 Graphics, and 24 GB Graphics Memory. All the programs were deployed in Python languages and implemented using Jupyter Notebook in Anaconda environment. OpenCV, Keras and Tensorflow packages were used to implement the deep learning model and their training.

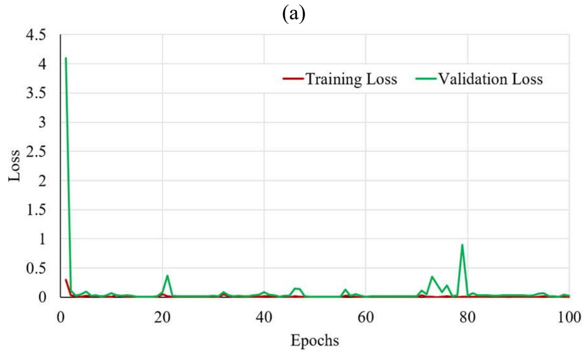
The dataset of fruit images in 12 different classes is separated into three different subsets i.e. training, validation and testing set. As the number of images were large, 11000 randomly chosen images in each class were used in the training set and 500 each is distributed among the validation set and test set. The validation set is given with the training set which helps the training model to tune its parameters accordingly and better fit the data points with good accuracy. The deep-learning trained model of Fruit-CNN for automated fruit classification and quality assessment is evaluated on images in the dataset after it has been trained for 100 epochs and the loss has been saturated. The experimental results confirmed the efficacy and resilience of the proposed Fruit-CNN model for fruit recognition and their quality detection.

An Adam optimizer was used as it utilizes a combination of both RMSprop and Gradient Descent with momentum, the learning rate hyper-parameter was set to 0.0001. Since the labels were encoded as one-hot vectors categorical cross-entropy was used as the loss function, the metric was accuracy. Then the model was fit using a batch size of 32, and the program was run up to 100 epochs to ensure the absence of extreme wavering or sudden crashes.

The training accuracy, validation accuracy, training loss, and validation loss were calculated and presented in Fig. 4. It is evident that as the number of epochs increases, both training and validation loss decrease and subsequently, the training and validation accuracy has been increased significantly. Highest validation accuracy of 100% and the lowest validation loss was obtained as 0.0023.




(a)




(b)

Fig. 4. Performance evaluation, (a) Accuracy curve, (b) Loss curve

Finally, an accuracy of 99.6% was achieved by the proposed model on the test set consisting of unseen images in different background and illumination conditions. A confusion matrix is a square grid consisting of the number of classes as the height and width, the more the sum of the numbers along the diagonal line from the top left to bottom right, the better performance of the system. This is because the quantity along these blocks gives the number of true positives, the images which were labelled as a particular class and the model predicted them as being such. The obtained confusion matrix on the test set is given in Fig. 5.

The performance comparison of the proposed Fruit-CNN architecture has been made with various state-of-the-art models i.e. Inception-Net [22], Mobile-Net [23], ResNet-50 [24], and VGG-19 [25]. The time taken to train completely was one of the metrics in which Fruit-CNN completely leap frogged state of the art models-taking only 45 minutes to train compared to the enormous times, most clocking in several hours for training. Table II shows a comparison of the performance of pre-existing state of the art models and the proposed Fruit-CNN. The given training time is with 24 GB Quadro P600 GPU and time will be much more when run on CPU or lower GPU processor. Hence, the proposed deep learning-based Fruit-CNN is computationally efficient and giving comparable accurate results with other state-of-the-art models. The proposed Fruit-CNN model took 3.83 seconds to test 500 images, resulting in 0.00766 seconds per images and around 130 frames per second.

As a result, the presented Fruit-CNN model allows for low-cost quality assessment and has broader potential uses in fruit quality prediction. The procedure is non-destructive and non-invasive, which serves to reduce fruit waste during quality control. Deep learning can be used to detect fruit quality quickly and quantitatively, and the proposed algorithmic framework might be used to detect other agricultural products as well.

TABLE II. PERFORMANCE COMPARISON OF PROPOSED FRUIT-CNN MODEL WITH OTHER STATE-OF-THE-ART MODELS

| **Model** | **Validation Accuracy (%)** | **Testing Accuracy (%)** | **Approximate Training Time (100 epochs)** |
|---|---|---|---|
| Inception-Net | 100 | 99.01 | 3 hours 3 mins |
| Mobile-Net | 100 | 99.40 | 7 hours |
| Mobile-Net-v2 | 100 | 99.21 | 8 hours 18 mins |
| ResNet-50-v2 | 99.8 | 99.60 | 3 hours 5 mins |
| VGG-19 | 100 | 99.01 | 6 hours 40 mins |
| Proposed Fruit-CNN | 100 | 99.60 | 47 mins |

## V. CONCLUSION AND FUTURE SCOPE

Defective fruits are the leading cause of financial crises in the agricultural farming business around the world. It has an impact on the standards and quality of fruits. Quality monitoring is a time-consuming and highly specialised post-harvest process. The need for a sufficiently fast and computationally less straining model which does not concede on excellent accuracy has been fulfilled through this proposed Fruit-CNN model. After training on 11,000 images and testing on 500 for validation and test each, this yields a 99.6% accuracy. This model has scope for further improvement as finding an even more optimum training time with almost no loss in accuracy could still be achieved, however even more promising than that is the prospect of using more classes for this model depending on the different varieties of fruits or even other crops that are grown all across India and the world. More types of fruits and crops to detect along with their quality has an implication in the form of higher widespread use of the technology, allowing for the classes to be

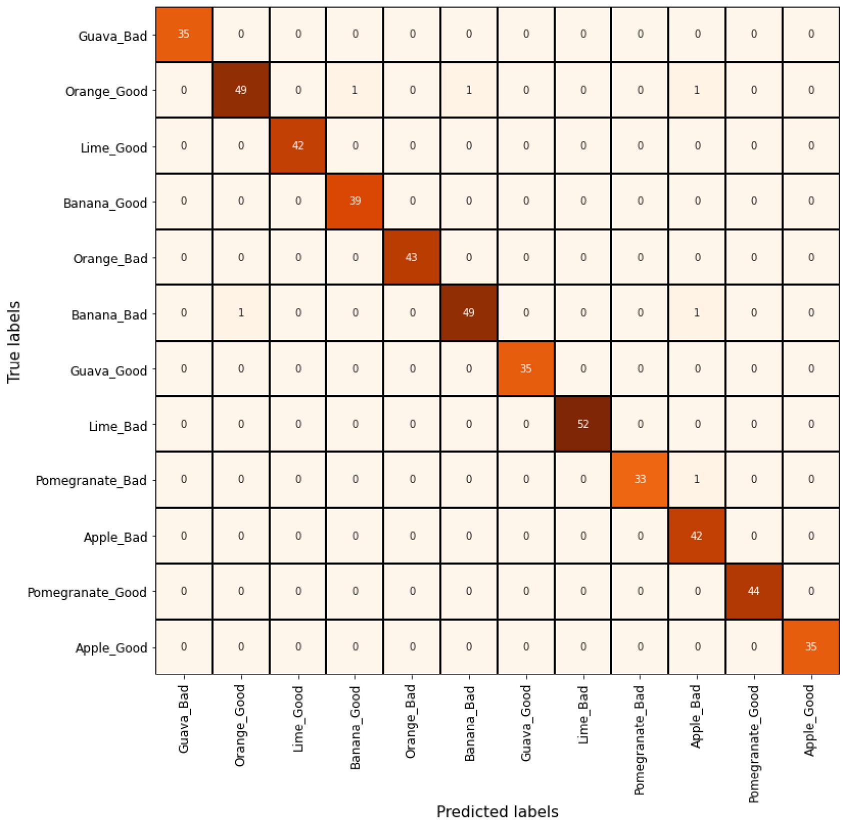



Fig. 5. Confusion matrix for the performance on test set of unseen images

dynamically adjusted according to the crops of the farmer, maximizing efficiency.

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