Online Grading of Fruits using Deep Learning Models and Computer Vision

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Abstract. Fruit quality evaluation is an important task in many industrial applications especially, in processing units. In Industries separating bad quality fruits manually is expensive and time consuming. The classification and grading of fruits when done manually is not precise. This work presents an efficient methodology for fruit classification using deep learning. Most existing works done to address the fruits classification based on quality focus on a single variety of fruit and a more general system with good accuracy is not available. In this paper, a Convolutional Neural Network based quality evaluation system for multiple fruits is presented. The proposed work is evaluated by comparing with state-of-the-art works based on two datasets and it achieves an accuracy of 99.12% and 97.67% for those. To make the proposed work available to public a web application has been created and the classification model is integrated to that.

INTRODUCTION

Fruits contribute to a large portion of nutrient intake and thus are an important part of human diet. The sale of fruits is impacted by quality of fruits, as customers prefer fresh fruits. Therefore, sorting fruits based on their quality is an important task. Although fruits can be sorted manually based on quality and freshness, the process will be slow and sometimes it will be full of errors. It's also difficult to monitor the quality of fruits manually. Another important motivation for analyzing the quality of fruits accurately is to avoid post-harvest loss. India suffers 10% loss of fruits annually [1]. This can be largely prevented by identifying the quality of fruits, segregating the good fruits and bad fruits and, if possible, treating and storing the fruits that may go waste. The grading of fruits for such purposes needs to be automated to efficiently process a huge quantity of fruits. In such cases, the analysis of the fruit quality will be a continuous task and computer vision systems are best suited for accurate analysis for quality assurance as they can perform classification of fruits, for in-creasing the market share for fruit industries and establish better quality standards. Therefore, this work aims to map the quality grading of fruits to an automated system by using deep learning to minimize the error and develop a system that is generalized for a number of fruit varieties. The following are the contributions of this paper:

- Development of a neural network model for classifying fruits based on their freshness and quality with high accuracy.
- Tuning the learning model to adapt for multiple varieties of fruits without impacting the accuracy.
- A web-based application that can be used for grading fruits based on their images.

RELATED WORK

In the past various works have been proposed for analysing the quality of fruits based on image processing techniques. To improve detection of abnormality in the fruit surface, multispectral and hyperspectral analysis have been proposed in earlier works [2-5]. A review on fruity quality evaluation algorithms [6] found that the use of multispectral or hyperspectral imaging techniques take a huge part in the quality evaluation techniques. However multispectral and hyperspectral imaging are costlier. A detailed survey of techniques employing spectral analysis for grading of agro products is presented in [7]. Another approach [8] used x-ray based imaging and segmentation to identify impurities and foreign objects in food items. Other methods also use segmentation to identify and narrow-down regions of infection in fruits and other produce [9-11].

Recently, computer vision based algorithms have gained attention due to their suitability for this particular task. A large number of recent computer vision based quality grading algorithms use pattern-based detection methodology. Table 1 lists some of the recent works that use machine learning for fruits quality evaluation. Each of the works used a different dataset and included different kinds of fruits. The dataset size before data augmentation is mentioned in the table. It can be seen from the table that neural network based algorithms are able to achieve higher accuracy when compared to traditional machine learning approaches.

TABLE 1. Recent works on fruits quality evaluation

Existing work	Fruit evaluated	Dataset size (image count)	Methodology	Accuracy (%)
Fan et al. [12]	Apple	3300	Convolutional Neural Network (CNN)	96.5
Bresilla et al. [13]	Apple, Pear	>5000	CNN - YOLO	90
Nandi et al. [14]	Mango	2184	Support Vector Machine (SVM)	87
Rokunuzzaman et al. [15]	Tomato	160	Rule based classifier	84
Ashok et al. [16]	Apple	65	Probabilistic Neural Network	88.33
Jagadeesh et al. [17]	General	-	Back Propagation Neural Network (BPNN)	89.15
Zhang et al. [18]	General	1653	Feed forward neural network (FNN)	89.1
Ismail et al. [19]	Apple, Banana	9091	EfficientNet	96.7 and 93.8
Priya et al. [20]	Apple	-	CNN	~97

PROPOSED WORK

In recent days, convolutional neural networks (CNN) are accepted to be more suitable for image recognition tasks [21]. The focus on CNNs has increased hugely and Deep Learning (DL) type of architectures based on CNN have gained high attention because of their ability to work well with images in a similar way to human brain. Deep learning has shown high accuracy with minimum error for solving complex problems [22]. CNN is advantageous over classic image processing techniques since it does not need pre-processing of the input images and can automatically extract the necessary features from the input images. With this observation, this work proposes to study the CNN architectures for classification of fruits based on their quality with the aim of achieving high accuracy.

As observed from the literature survey, the previous works done for fruits quality evaluation have analyzed their models on either very small dataset or for a particular kind of fruit. Deep neural networks train better with larger datasets and may overfit on smaller datasets. Therefore, using smaller dataset may lead to overfitting and the performance of the resulting architecture may be overestimated because the absence of enough variations in the training samples [23].

Thus, with the aim of finding a fast and accurate deep neural network model that generalizes well for larger dataset with more fruit varieties, the proposed work has been carried out.

Dataset

The datasets listed in table 2 were used for analyzing the proposed work. The Fruits fresh dataset [24] is a publicly available dataset that was captured by placing the fruits in the shaft of a low-speed motor and recording a short video of 20 seconds. Then the images were collected from the video frames. The second dataset used is

FruitsGB [25] containing 12 classes. The dataset comprises of thousand images of dimension 256x256. The images are diverse with varying background, lighting and rotation angle.

TABLE 2. Dataset description

Dataset Feature	Fruits fresh [24]	FruitsGB [25]
Number of training samples	10901	9600
Number of validation samples	2698	2400
Number of classes	6	12
Class Labels	Fresh apple, spoiled apple, fresh banana, spoiled banana, fresh orange, spoiled orange	Fresh apple, spoiled apple, fresh banana, spoiled banana, fresh orange, spoiled orange, fresh guava, spoiled guava, fresh lime, spoiled lime, fresh pomegranate, spoiled pomegranate

Image Preprocessing

Using deep neural networks for image classification gets rid of the need for pre-processing the image that includes steps such as segmentation, feature extraction, etc. The layers of the deep neural network can learn high-level features from the training data automatically. When using CNNs for deep learning, the layers are capable of extracting features such the edges in the earlier layers and advanced textures and shapes in the later layers [26]. As the proposed work used deep neural networks, image preprocessing was not needed. However, to increase the size of the dataset and to make the training sample divergent, data augmentation was performed [27]. Each of the training image was augmented to form four new samples. This was done by applying rotation, shifting, and resizing operations. For rotation a random rotational degree was chosen and the training sample was rotated accordingly. Similarly, two kinds of shifting operations were done to shift the image along its length and its width thereby producing two more samples. Finally, scaling was done based on a randomly chosen value and then zooming on the training image, without exceeding the original size of the image.

Deep Neural Network

The work started with building a traditional deep neural network for classification of good and bad fruits. This network termed DNN is implemented with simple forward and back propagation algorithms. The 3 layered neural network model DNN was trained on a Fruits fresh dataset which consists of 6 classes. The model is summarized in table 3.

TABLE 3. DNN model summary

Parameter	Value
Hidden Layer 1	250 nodes
Hidden Layer 2	150 nodes
Output Layer	6 nodes
Activation Function	Softmax
Loss Function	Cross entropy loss

Proposed CNN Model

CNN [26] is a neural network architecture with multiple layers viz. input layer, convolutional layer, max-pooling layer, and classification layer which does feature extraction and classification. The feature map layers of the CNN apply convolution filtering and down sampling operations to learn features such as pattern, texture, and color from the input sample. The classification is done typically with fully-connected layers after feature extraction. Backpropagation will be applied to adjust the weight learned for feature extraction and classification.

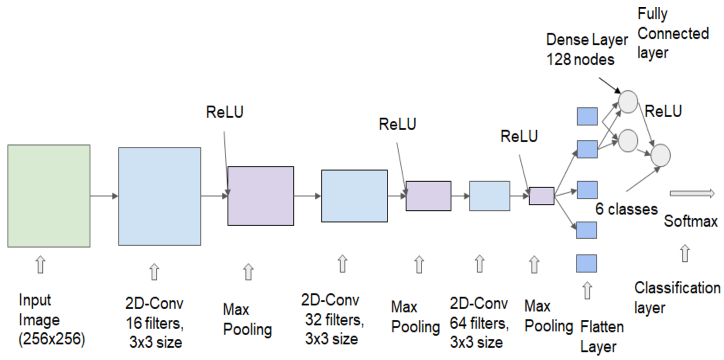


FIGURE 1. FQNet-1Architecture

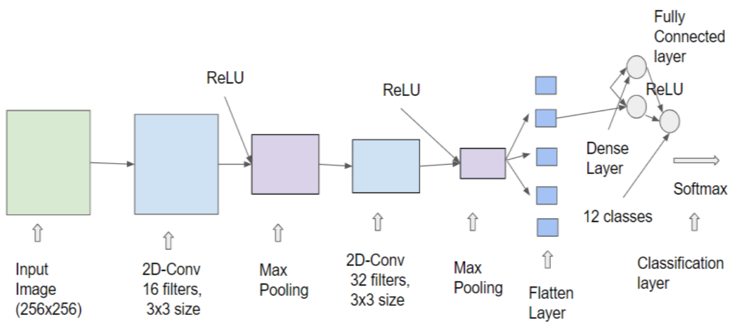


FIGURE 2. FQNet-2Architecture

The CNN model shown in Fig. 1 was created to improve the prediction accuracy from the traditional DNN. The model has 3 layers as given by table 4. Although this CNN model (FQNet-1) was able to evaluate fruits quality with better accuracy, when tested on a huge dataset it did not fare well as discussed in the later results section. After implementing FQNet-1, a noticeable difference between training accuracy and validation accuracy was observed. Figure 2 gives the improved CNN (FQNet-2) obtained after further parameter tuning. The parameter tuning was done by inspecting the results of the FQNet-1. The results showed trends of overfitting and to avoid that number of parameters were reduced by reducing the neurons [28]. This is achieved removing layers to get the improved model. The tuning was done by trial and error and the layers were adjusted until the overfitting effect was removed during validation. Overfitting can also be caused due to the smaller size of dataset and noise. Adam optimizer has shown to outperform gradient descent for sparse gradients and noisy problems [29]. Therefore, Adam optimizer is used for FQNet-2. This new architecture yielded better validation accuracy when compared to FQNet-1. The detailed results are discussed in the next section. Table 4 lists the parameters of FQNet-1and FQNet-2.

TABLE 4. Summary of CNN models

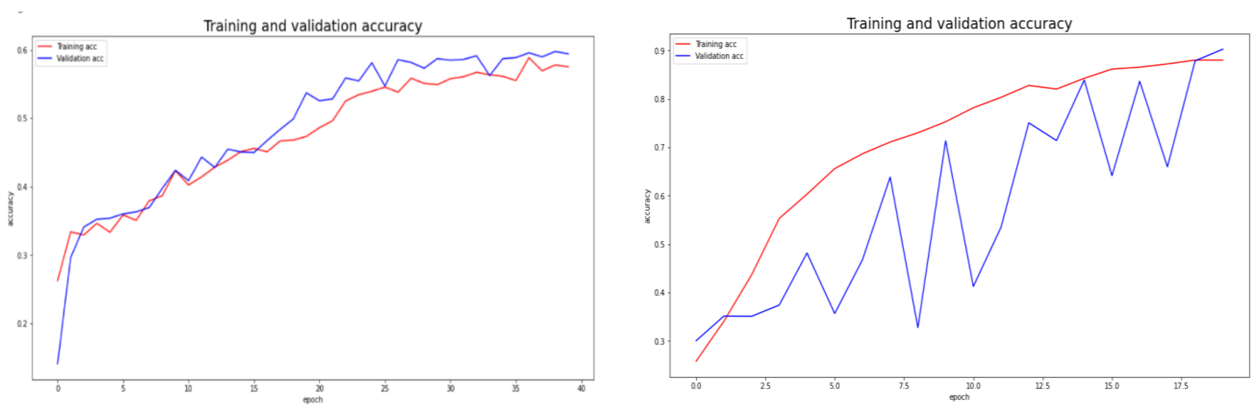
Parameter	FQNet-1	FQNet-2
Layer 1	16 filters, filter size 3x3, Max pooling, ReLU activation	16 filters, filter size 3x3, Max pooling, ReLU activation
Layer 2	32 filters, filter size 3x3, Max pooling, ReLU activation	64 filters, filter size 3x3, Max pooling, ReLU activation
Layer 3	64 filters, filter size 3x3, Max pooling, ReLU activation	-
Dense Layer 1	128 nodes	128 nodes
Dense Layer 2	6 nodes	6 nodes
Classification	Softmax	Softmax
Optimizer	Gradient descent	Adam
Loss function	Cross Entropy Loss	Cross Entropy Loss

RESULTS AND DISCUSSION

This section discusses the experiments conducted to verify the proposed model and the results observed. The proposed algorithm is implemented on Intel Core-I7 CPU with 8 GB RAM, NVIDIA Geforce MX350 GPU, and Windows operating system. The implementation was done using Tensorflow and Keras. The parameters for the CNN and Adam optimizer were set to the default values as given by Tensorflow.

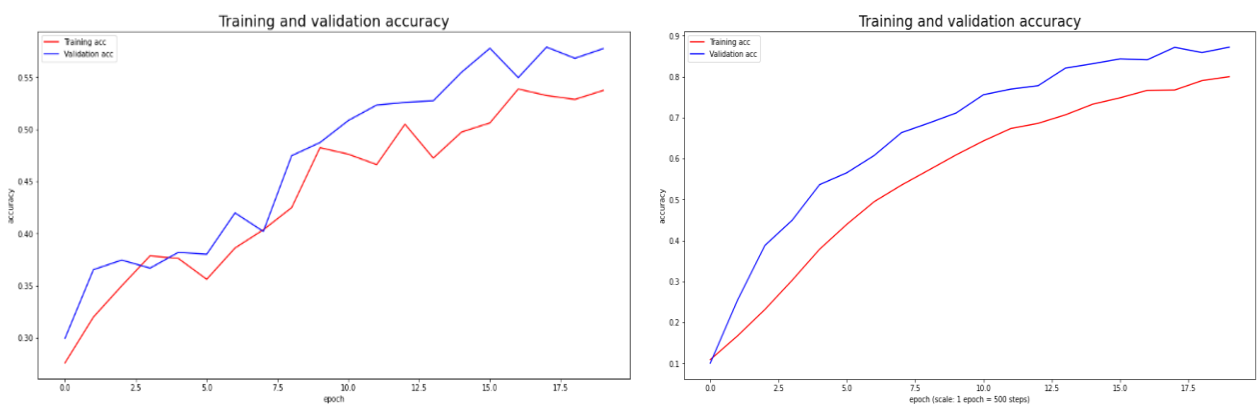
Performance of Existing Approaches to Detect Fruit Quality

The performance of traditional deep neural networks along with the performance of existing state-of-the-art models that use deep learning [12], [13] are studied with respect to the FruitsGB and Fruits fresh dataset. The existing works and the proposed model were all implemented and tested on these common datasets to have a fair comparison. In [12] a CNN architecture with one input layer, three convolutional layers, two pooling layers, and a classification layer is proposed. The proposed architecture was designed to find the quality of a single type of fruit – apple. Therefore, even though it performs well in detecting the quality of apples, the model did not generalize well for other kinds of fruits and has achieved only 58% accuracy for Fruits fresh dataset, as given by table 5; Figure 3 gives the accuracy plot for the two datasets. In [13] a YOLO convolutional network is used for identifying fruits in a tree. With the use of YOLO, the model in [13] has shown a faster detection however, the accuracy of the model is comparatively less i.e. 87%. Figure 4 shows the accuracy curve for [13] on the two datasets.



(a) (b)

FIGURE 3. Accuracy curves of existing work [12] for (a) FruitsFresh and (b) FruitsGB



(a) (b)

FIGURE 4. Accuracy curves of existing work [13] for (a) FruitsFresh and (b) FruitsGB

Performance of CNN Approach to Detect Fruit Quality

To compare the robustness of the proposed model with existing works, Fig. 5 shows the accuracy and loss curves of FQNet-1 for the two datasets. Figure 6 shows the accuracy and loss curves of FQNet-2 for both the datasets. The training took a long time because of the size of the dataset and in order to obtain correct results the number of epochs was appropriately chosen for each model until it stabilizes. The loss and accuracy are better for FQNet variations when compared to the existing approaches as shown by the Fig. 3 and 4. In particular [13] has overfit the data for FruitsFresh dataset and [12] has resulted in overfitting for the FruitsGB dataset. FQNet-2 achieves a better accuracy compared to FQNet-1 and reaches more than 99% and 97% accuracy for FruitsFresh and FruitsGB datasets respectively. Table 5 summarizes the accuracy values and table 6 gives the loss values for the different models for both the datasets.

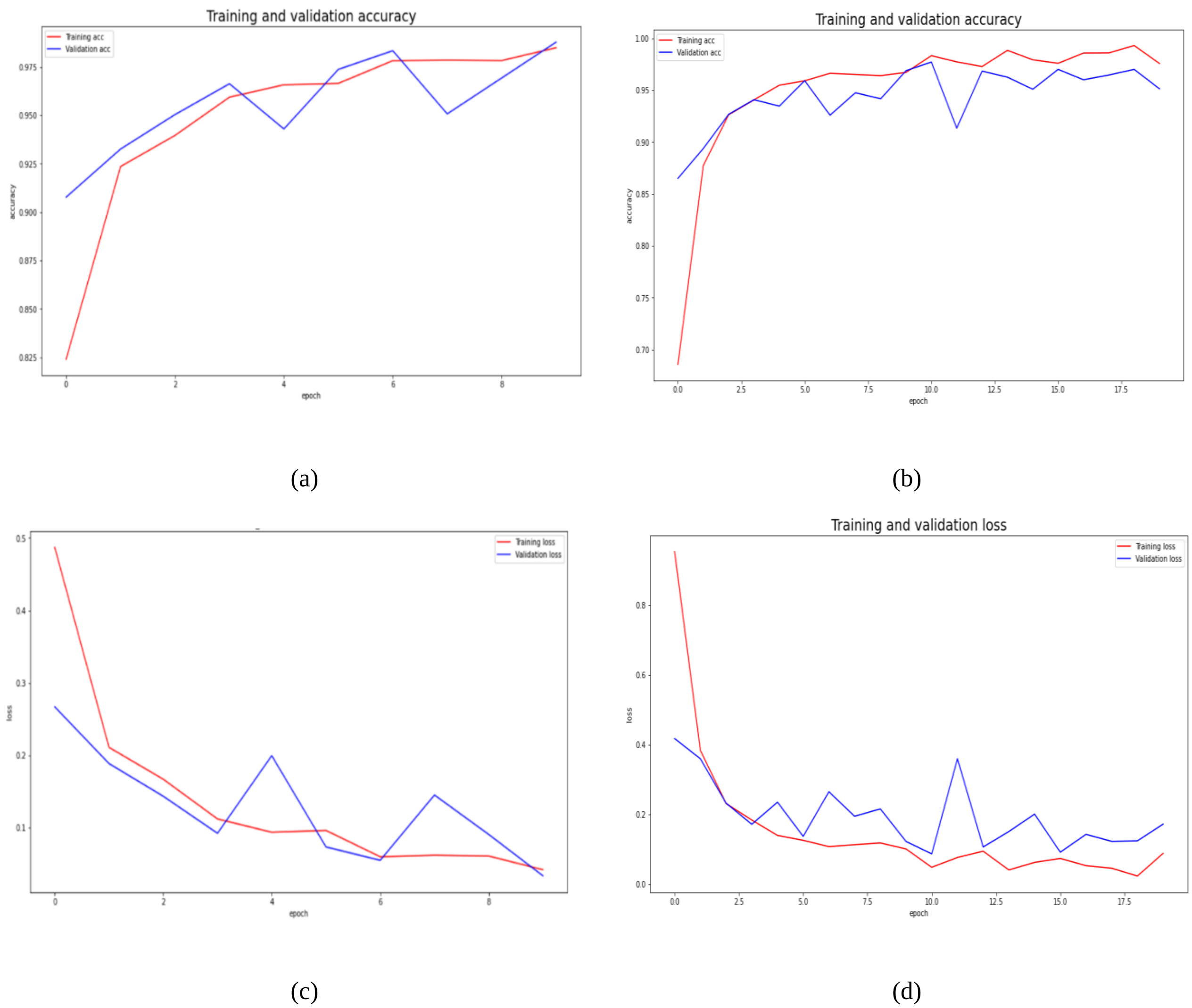
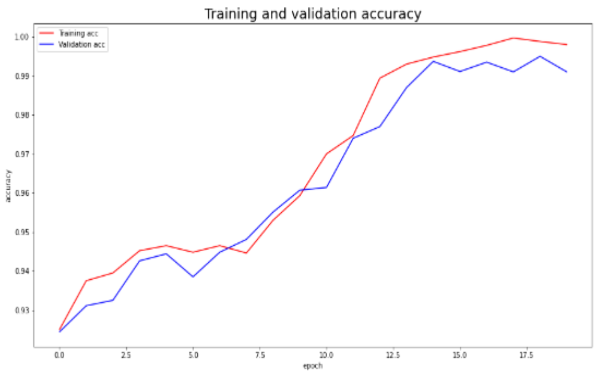
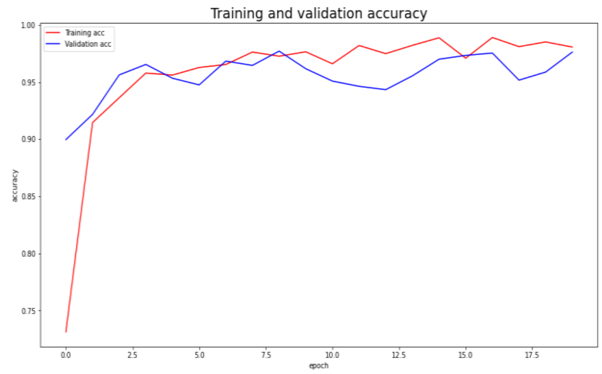


FIGURE 5. Accuracy curves of FQNet-1 for (a) FruitsFresh (b) FruitsGB and Loss curves for (c) FruitsFresh (d) FruitsGB



(a)



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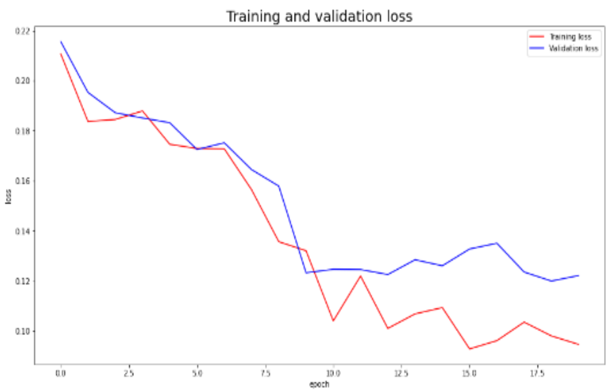
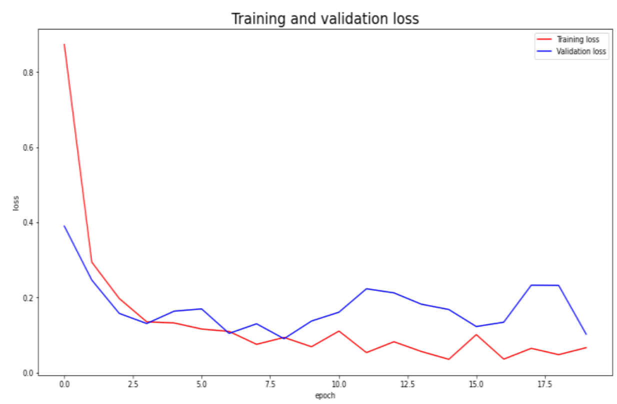


(c)



(d)

FIGURE 6. Accuracy curves of FQNet-2 for (a) FruitsFresh (b) FruitsGB and Loss curves for (c) FruitsFresh (d) FruitsGB

TABLE 5. Accuracy of existing and proposed works in percent

Model	**FruitsFresh**		**FruitsGB**	
	Training Loss	**Validation Loss**	**Training Loss**	**Validation Loss**
DNN	0.64	1.21	1.53	2.04
[12]	1.14	1.15	0.30	0.33
[13]	1.11	1.11	0.45	0.44
FQNet-1	0.06	0.05	0.13	0.20
FQNet-2	0.09	0.12	0.1	0.16

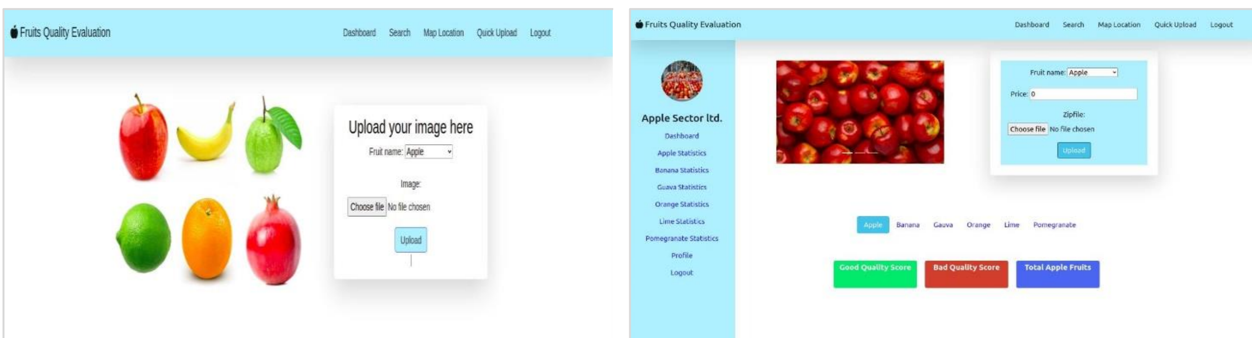
Web Application

After developing the FQNet-2 model, a web application was built for providing fruit grading service and the proposed model was integrated into it. Due to the simplicity of the FQNet-2 the web application was able to predict the fruit quality in minimal time. Figure 7 shows the web page for uploading a fruit image which will be classified using the proposed model. Apart from the fruits classification, the following functionality were also included in the application.

- Bulk grading – Option to upload a folder of fruit images that will be classified and results available in .xlsx format for each fruit as shown in Fig. 7.
- Download dataset option – All the images uploaded will be added to the database and users can request and download the dataset.
- Statistics – For every user, the daily statistics can be viewed which will show the history of previous fruit identification as a percentage of bad fruits.

TABLE 6. Loss for existing and proposed works in percent

Model	FruitsFresh		FruitsGB	
	Training	**Validation**	**Training**	**Validation**
DNN	81.68	80.24	78.51	80.24
[12]	58.56	58.08	90.53	90.25
[13]	94.75	93.88	87.21	87.31
FQNet-1	99.43	98.78	97.52	95.29
FQNet-2	99.83	99.12	99.21	97.67



(a) (b)

FIGURE 7. (a) Webpage to upload fruit image for classification (b) Webpage for bulk upload of fruit images as an archive folder to be classified

CONCLUSION

This paper presented a Convolutional Network model for classifying different fruits based on their quality. Although the existing CNN models perform well for smaller dataset they did not generalize suitably for a larger dataset. The proposed model was arrived at after tuning the architecture and the study showed that simpler architecture was able to generalize well for a dataset when compared to a larger architecture. The proposed model was compared with existing state-of-the-art CNN models based on its accuracy. The results show that the proposed model is able to achieve an average of 98.4% accuracy for two datasets. A web application was developed to integrate and validate the proposed model. The future works will focus on grading the fruits based on their maturity to identify and preserve fruits before they start turning bad.

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