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Implementation of Deep Learning Methods to Identify Rotten Fruits

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***Abstract*— Mostly in the agriculture sector, identifying rotten fruits has been critical. The classification of fresh and rotting fruits is typically carried out by humans, which is ineffective for fruit growers. Humans wear out by doing the same role many days, but robots do not. As a result, the study proposed a method for reducing human effort, lowering production costs, and shortening production time by detecting defects in agricultural fruits. If the defects are not detected, the contaminated fruits can contaminate the good fruits. As a result, we proposed a model to prevent the propagation of rottenness. From the input fruit images, the proposed model classifies the fresh and rotting fruits. We utilized three different varieties of fruits in this project: apple, banana, and oranges. The features from input fruit images are collected using a Convolutional Neural Network, and the images are categorized using Max pooling, Average pooling, and MobileNetV2 architecture. The proposed model's performance is tested on a Kaggle dataset, and it achieves the highest accuracy in training data is 99.46% and in the validation set is 99.61% by applying MobileNetV2.The Max pooling achieved 94.49% training accuracy and validation accuracy is 94.97%. Besides, the Average pooling achieved 93.06% training accuracy and validation accuracy is 93.72%. The findings revealed that the proposed CNN model is capable of distinguishing between fresh and rotting fruits.**

Keywords—rotten fruit detection; CNN; max-pooling; average pooling; MobileNetV2; deep learning

I. INTRODUCTION

Computer vision approaches have improved the efficiency of image classification tasks, particularly in the fields of machine learning [1] and deep learning [2-6]. One of the main problems in the agricultural fields is the detection of defective fruit and the identification of new and rotten fruits. If not correctly classified and can also impact productivity, rotten fruits can cause harm to other fresh fruits. This designation is traditionally performed by hard-working men, time-consuming and not effective. Moreover, manufacturing costs are often increased. We also need an integrated system that reduces human efforts, increases productivity, and reduces production costs and production time.

In the paper [7], a CNN model is proposed for feature extraction from an input image of fruits that are apple, banana, and orange. For classification, a Softmax classifier is used on the images. To compare the accuracy with the proposed model, VGG16, VGG19, Xception, and MobileNet transfer learning models are used which shows that the proposed model exceeds in accuracy. K. Roy et al. [8] proposed a method that implements the segmentation technique to detect rotten fruits. Marker-based segmentation, color-based segmentation, and edge detection techniques are utilized after the image data is converted to greyscale, and filtering and thresholding to reduce noise. In the final output, rotten fruit is detected and marked. The authors in the paper [9] proposed a semantic segmentation technique using uNet and En-UNet deep learning architecture to detect rotting in fruit from image data. Before training the data, it is converted to greyscale from the raw RGB image and later masked by using thresholding and inverse binarization. Finally, the obtained masked binary image is trained using the deep learning [10-11] methods. The objective of the paper [12] is to propose a method that uses a segmentation method to detect rotten or fresh fruits. The image of the fruits is rectified by detecting the foreground using 'YCbCr' color space.to segment out the essential portion of the image, 'L*a*b*' color space and KNN clustering method is used. Finally, to identify the rotten portion, segmentation is done using a color map.

The rest of the paper is in the same arrangement. The most rapid current developments in rotten fruits identification are discussed in this sector. Section II describes the analytical methodology for the construction of the whole system. The result of the structure produced is examined in Section III. Section IV finishes with observation and deficiencies and plans for potential work.

II. Research Methodology

Bangladesh's agriculture sector is most significant. The agriculture sector of Bangladesh accounts for 14.2% of the GDP of Bangladesh, providing 42.7% of working countries with employment. It is necessary to eliminate the possibility of foodborne disease in order to improve the average longevity of human beings. People in a risky community depend mostly on fruit and vegetables. It is therefore essential to distinguish rotting or fruits from healthy ones in order to ensure their protection. Automation technology is an integral part of life nowadays. Bangladesh is a nation dependent on agri-based farming. Agriculture is their principal source of wealth. The selling is widening every day of fresh fruit. Health-conscious people choose only healthy raw fruits of quality.

The 21st century is seeing an increasingly dynamic role in the fruit and food manufacturing sectors [13]. Global exchange and fruit and vegetable demand flow decide the proximity between exporters and importers. For the exportation or importation of rotten or almost rotten fruit, there is a long and time-consumed transportation method that impedes quality control of a vast number of fruits. As a result, fruit output is expected to fall more compared with the world fruit production and trade of previous years. Other main causes of concern behind the decline in commerce are not just all other challenges, but also volatile environment trends, climate change, and temperature growth. Besides, the food industry has been seriously impaired, aside from the export and importation of fresh fruits, due to the monitoring of the nature of the rotten fruit.

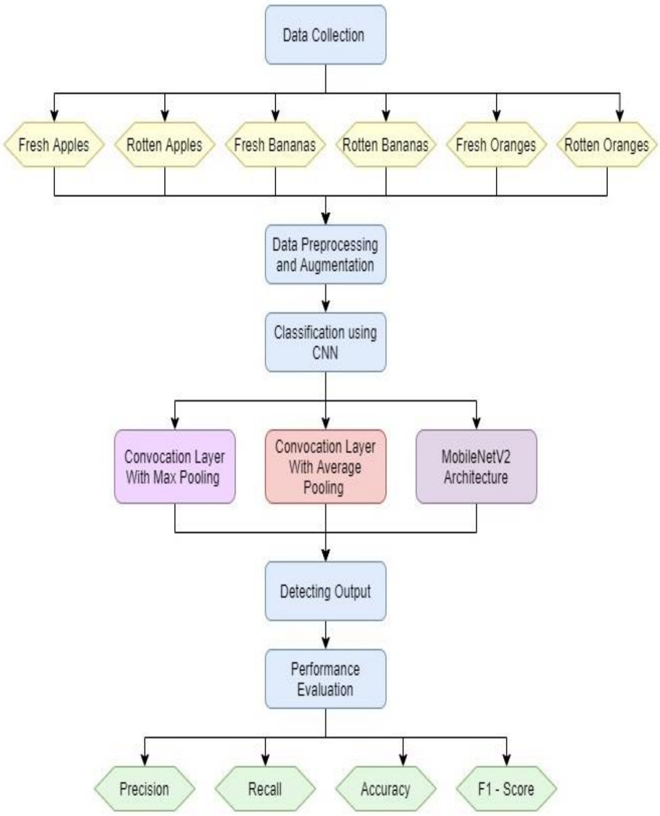

Fig. 1. Proposed System diagram.

A. Dataset Collection:

We used a dataset from kaggle.com for this study. At first, the dataset is fresh fruits and rotten fruits for classification (https://www.kaggle.com/sriramr/fruits-fresh-and-rotten-for-classification). The data set is divided into 6 categories, as follows:

- Fresh Apples
- Fresh Oranges
- Fresh Bananas
- Rotten Apples
- Rotten Oranges
- Rotten Bananas

The dataset contains 13599 images that were used for validation and training.

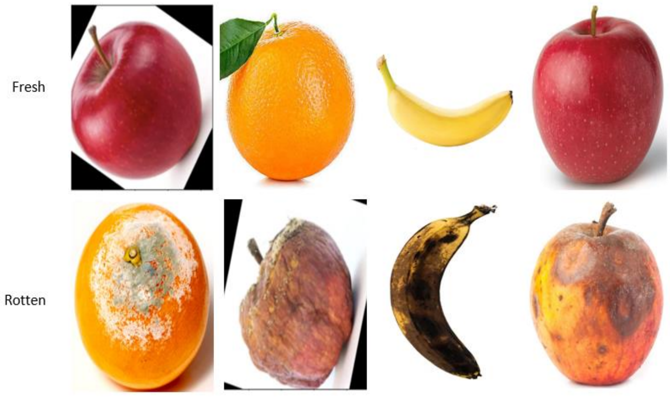

Fig. 2. Datasets Images Sample.

B. Preprocessing and augmentation of Data :

The images in the dataset are not all the same size, so preprocessing was needed for this study. Deep learning [14-16] models require a significant amount of data for training rather than machine learning [17-21]. We used Keras' ImageDataGenerator tool to resize all of the images to 256 x 256 pixels. We normalized both images after transforming them to 256 X 256. For faster calculation, images are converted to NumPy arrays. The volume of data may be increased by rotating, zooming, shearing, and flipping horizontally. Photos are obtained as well. The photos are then reshaped into 128 x 128 pixels for passing into the second convolution layer, and then down to 64 x 64 pixels for passing into the third convolution layer.

C. Proposed Convolution Neural Network (CNN) architecture

For classification and image recognition, CNN is used. One or two convolution layers compose a CNN. Rather than dealing with the entire picture, CNN tries to identify elements that are useful inside it. There are several hidden layers in CNN, as well as an input layer and an output layer. In this study, we used a deep CNN with three convolution layers. Convolution is a technique for merging two mathematical functions to create a single one. Our CNN model's working process is depicted in Fig. 3.

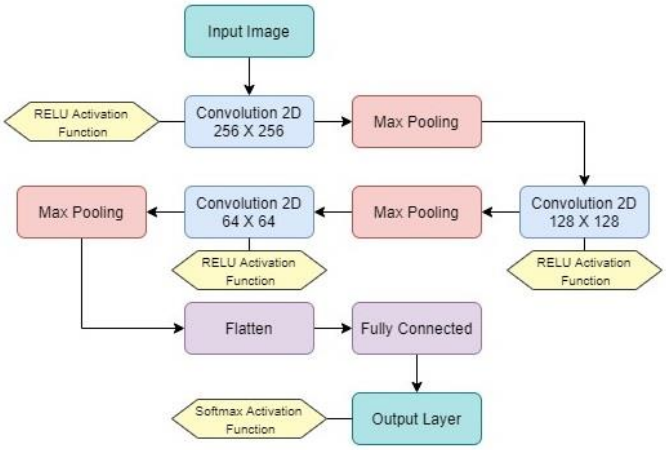

Fig. 3. Three Convolution Layer with Max pooling operation.

Again, the same architecture is applied with average pooling operation for feature mapping this time. Fig. 4 demonstrates the working procedure of the model. Max pooling takes the highest number inside the region of interest of the image matrix where Average pooling takes the average of all values of that region. Our CNN model initiates with Keras.models.sequential(). Relu activation function is applied in the first hidden layer then Max pooling operation is applied. Max pooling helps to gather significant information and reduces the size of the images. Then the data is passed to the second convolution layer. For getting the most notable information max pooling is applied again. The obtained image matrix is then flattened and trained. For observing the performance of the model, we trained our model with the Average pooling operation instead of the max pooling operation. Adam stochastic gradient descent algorithms have been used for training with better accuracy. For training purposes, we use 80% images of our dataset.

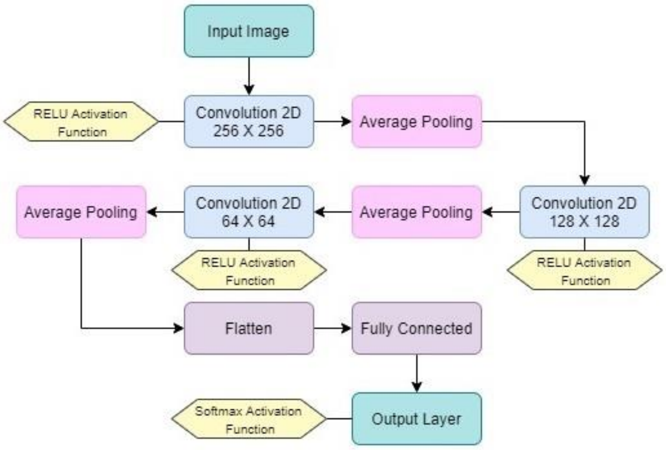

Fig. 4. Three convolution layers with Average Pooling operation.

D. MobileNetV2 Architecture

MobileNetV2 is extremely effective for image classification. MobileNetV2 is a lightweight deep learning model built on the CNN that provides the weight of the image through TensorFlow. The base layer is first stripped and a new trainable layer is applied to MobileNetV2. The model operates on the data collection obtained and defines the most correlated features of our images. MobileNetV2 is consisting of 19 layers of bottleneck [22]. OpenCV, which uses ResNet-10 in the base model [22], was included. Caffemodel from OpenCV is used to detect the front side of a fruit image. Then it extracts the knowledge needed and transmits it to the fruit classifier layer Overfitting in machine learning is a significant concern. For ignoring our model to be overfitted with the dataset we have used the Dropout layer. With MobileNetV2 (include top=False) we removed the base layer. The photos have been reshaped. Our model contains 256 hidden layers and is implemented with a pool size average pooling operation (7,7). Relu activation function is applied in the hidden layer and softmax activation function in the fully connected layer. Relu activation function is applied in the hidden layer and softmax activation function in the fully connected layer. We define a learning rate of 0.001 for better accuracy. Adam's stochastic gradient descent algorithm helps the model for a better understanding of image features. MobileNetV2 working layer depicted in Fig. 5.

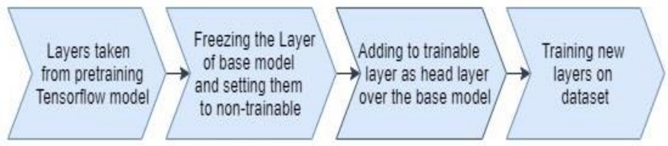

Fig. 5. MobileNetV2 Architecture.

E. Evaluating performance using performance matrix:

After completing the training and testing phase, we have measured the performance of two models using precision, recall, f1-score, and accuracy. We have used the following formula's,

$$Precision = \frac{TP}{TP+FP} \quad (1)$$

$$Recall = \frac{TP}{TP+FN} \quad (2)$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \quad (3)$$

$$F1 - Score = \frac{Recall*Precision}{Recall+Precision} \quad (4)$$

III. EXPERIMENTAL RESULT ANALYSIS:

For detecting fresh and rotten fruits from images we have used a dataset consist of 13599 images. Table I describes the training accuracy and validation accuracy after applying the Deep CNN model where Max Pooling is applied to reduce the dimension of our image feature map. The highest accuracy in training data is 94.49% and in the validation set is 94.97%.

TABLE I. OUTCOMES FOR DEEP CNN AFTER APPLYING MAX POOLING OF DIFFERENT EPOCHS

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	47.13%	87.36%	15.37%	89.99%
2	12.01%	88.17%	10.13%	90.32%
3	9.45%	88.39%	9.01%	91.04%
4	8.81%	90.58%	6.88%	91.70%
5	8.04%	90.65%	6.55%	91.83%
6	7.40%	91.04%	6.16%	92.33%
7	7.33%	91.12%	5.98%	92.83%
8	6.91%	91.95%	5.77%	93.26%
9	6.76%	93.01%	5.14%	93.72%
10	6.23%	93.87%	5.04%	94.08%
11	5.97%	94.04%	4.84%	94.36%
12	5.89%	94.48%	4.67%	94.71%
13	5.84%	94.49%	4.12%	94.97%

Fig. 6 shows the training accuracy and validation accuracy graph. The same CNN architecture is applied later where Average Pooling is used to reduce the dimensions of feature map. The predicted result shows less accuracy than the previous model. Table II shows the predicted outcomes where maximum training accuracy is 93.06% with a training loss of 6.96% and the validation accuracy is 93.72%.

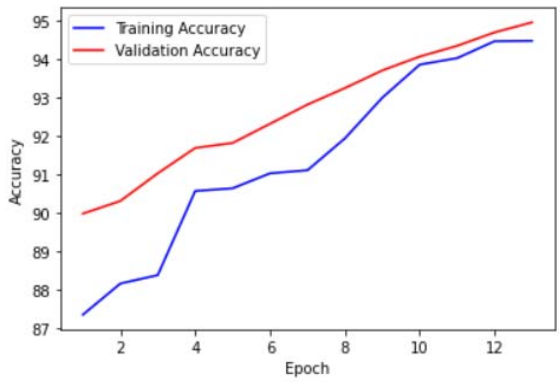

Fig. 6. Test Accuracy and Training Accuracy for CNN with Max Pooling Layer.

TABLE II. OUTCOMES FOR DEEP CNN AFTER APPLYING AVERAGE POOLING OF DIFFERENT EPOCHS

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	44.12%	86.89%	11.12%	88.23%
2	12.65%	87.12%	10.76%	88.87%
3	12.23%	87.46%	8.24%	89.41%
4	11.42%	89.02%	8.14%	89.95%
5	11.05%	89.26%	8.04%	90.12%
6	10.24%	89.95%	7.64%	91.23%
7	9.65%	90.00%	7.34%	91.42%
8	8.98%	91.14%	7.16%	92.77%
9	8.97%	91.14%	7.08%	92.83%
10	8.76%	91.24%	7.03%	92.91%
11	7.25%	92.54%	6.53%	93.13%
12	7.10%	92.88%	6.34%	93.62%
13	6.96%	93.06%	5.28%	93.72%

Fig. 7 shows the graph of relative validation accuracy and training accuracy for each epoch.

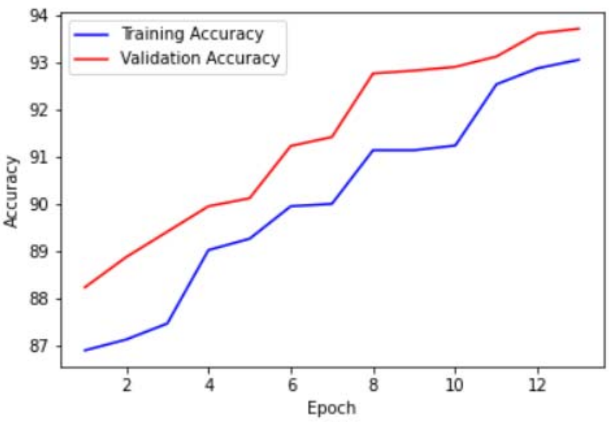

Fig. 7. Test Accuracy and Training Accuracy for CNN with Average Pooling Layer.

After applying MobileNetV2 architecture the accuracy improved significantly. Table III describes the validation and test accuracy concerning each epoch.

TABLE III. DIFFERENT OUTCOMES AFTER APPLYING MOBILENETV2 ARCHITECTURE

Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
1	4.53%	98.02%	4.21%	98.75%
2	4.36%	98.03%	4.12%	98.81%
3	4.32%	98.14%	4.09%	98.92%
4	4.26%	98.24%	3.89%	99.01%
5	3.23%	98.52%	3.72%	99.05%
6	3.96%	98.59%	3.61%	99.12%
7	3.46%	98.71%	3.56%	99.42%
8	3.43%	98.92%	3.41%	9946%
9	3.25%	98.98%	3.23%	99.52%
10	3.24%	99.12%	3.20%	99.55%
11	3.22%	99.43%	3.18%	99.57%
12	3.22%	99.45%	3.18%	99.58%
13	3.15%	99.46%	3.18%	99.61%

From Table III, the highest accuracy is achieved at 99.46% for validation data and 99.61% for training data. The data loss in the validation phase is only 3.15%. Fig. 8 shows the detailed comparison of test accuracy and validation accuracy of MobilenetV2 which is a CNN-based architecture. We have also calculated the confusion matrix after applying MobilenetV2 architecture. Table IV describes the confusion matrix properly.

TABLE IV. CONFUSION MATRIX AFTER APPLYING MOBILENETV2

Class	Precision	Recall	F1 - Score
0 [Fresh Apples]	98%	99%	97%
1 [Fresh Oranges]	99%	99%	99%
2 [Fresh Bananas]	99%	98%	97%
3 [Rotten Apples]	98%	99%	98%
4 [Rotten Oranges]	99%	99%	99%
5 [Rotten Bananas]	99%	98%	98%

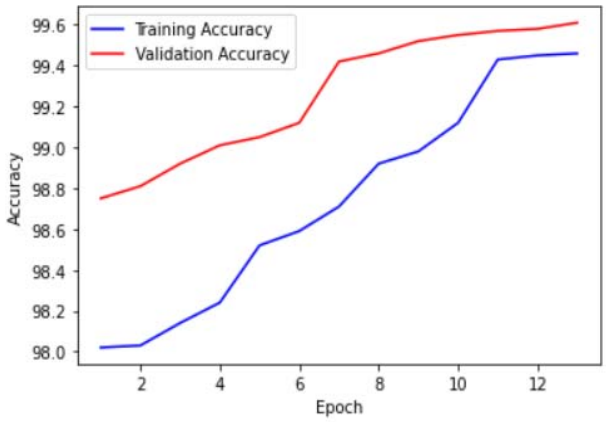

Fig. 8. Test Accuracy and Training Accuracy for MobilenetV2 with Average Pooling Layer

The MobilenetV2 design outperformed many of the other models included in this study. This model is capable of recognizing the mask in a picture. In Fig. 9 and 10 showing the detection result of MobileNetV2.

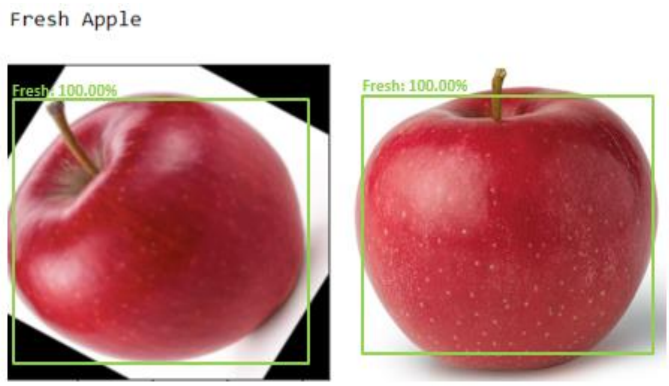

Fig. 9. Detection of fresh apples from dataset images.

Fig. 10. Detection of rotten apples from dataset images.

The Max pooling achieved 94.49% training accuracy and validation accuracy is 94.97%. Besides, the Average pooling achieved 93.06% training accuracy and validation accuracy is 93.72%. MobileNetV2 architecture gained the highest accuracy 99.46% for training and 99.61% for validation. A short explanation is added in Table V.

TABLE V. COMPARISON WITHIN THE CNN TECHNIQUES

	Epoch	Training Loss	Training Accuracy	Validation Loss	Validation Accuracy
Max Pooling	13	5.84%	94.49%	4.12%	94.97%
Average Pooling	13	6.96%	93.06%	5.28%	93.72%
MobileNetV2	13	3.15%	99.46%	3.18%	99.61%

IV. CONCLUSION AND FUTURE WORK

In the fruit processing industry, computer vision has a broad variety of uses, enabling processes to be automated. For the industry manufacturing unit to produce the highest quality finished food products and the finest quality raw fruits to be able to be sold in the sector, classification of fruit quality and thus grading of the same is very necessary. In this study, we used two deep CNN architectures and one CNN-based MobilenetV2 architecture in this study. Our main goal was to propose a suitable model with high accuracy such that fruit detection could be simplified in the agricultural sector. In order to assess performance with a wider dataset, we can attempt to add further models to compare with Mobilenetv2. In the future, we will integrate this model with IoT [23-27] to detect rotten fruits automatically by AI and IoT.

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