International Journal of Engineering and Management Research
www.ijemr.net
e-ISSN: 2250-0758 | p-ISSN: 2394-6962
Volume-12, Issue-5, (October 2022)
https://doi.org/10.31033/ijemr.12.5.2

A Deep Learning based Model for Fruit Grading using DenseNet

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ABSTRACT

Detecting the rotten fruits become significant in the agricultural industry. Usually, the classification of fresh and rotten fruits is carried by humans is not effectual for the fruit farmers. Human beings will become tired after doing the same task multiple times, but machines do not. Thus, this paper proposes an approach to reduce human efforts, reduce the cost and time for production by identifying the defects in the fruits in the agricultural industry. If we do not detect those defects, those defected fruits may contaminate good fruits. Hence, we proposed a model to avoid the spread of rottenness. The proposed model classifies the fresh fruits and rotten fruits from the input fruit images. For this work, we have used three types of fruits, such as apple, banana, and oranges. A Convolutional Neural Network (CNN) is used for extracting the features from input fruit images, and Softmax is used to classify the images into fresh and rotten fruits. The performance of the proposed model is evaluated on a dataset that is downloaded from Kaggle and produces an accuracy of 97.82%. The results showed that the proposed CNN model can effectively classify the fresh fruits and rotten fruits.

Keywords— Agricultural Industry, CNN, Pre-Trained Models, Softmax

I. INTRODUCTION

Recent approaches in computer vision, especially in the field of deep learning, have improved the efficiency of image classification tasks. Detecting defective fruit and sorting between fresh and rotten fruit is one of the biggest challenges in agriculture. Rotten fruit, if not properly sorted, can damage other fresh fruit and can also affect productivity. Traditionally, this sorting is done by men which was a labor-intensive, time-consuming and not efficient process. It also increases production costs. Therefore, there is a need for an automated system that can reduce human effort, increase production, and reduce production costs and production time.

II. MATERIAL AND METHODS

Dataset Acquisition and Pre-Processing

The dataset is obtained from Kaggle which has three types of fruits apples, bananas, and oranges with 6 classes i.e. each fruit divided as fresh and rotten. The total size of the dataset used in this work is 13599 images. The training images are of 10,901, and the test set contains of 2698 images which belong to 6 classes. The samples for each class in the dataset are shown Figure 1.

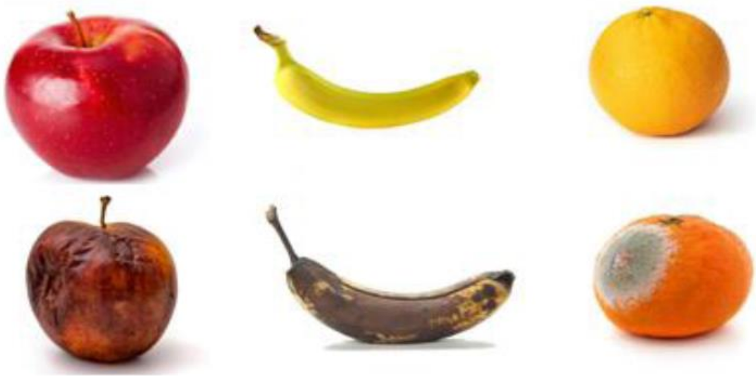

Figure 1: Sample dataset

Workflow

Firstly we are collected our image data. It was challenge for us in covid situation. Then we are data preprocessing and we build a CNN model. Then we train CNN model and evaluate our model.

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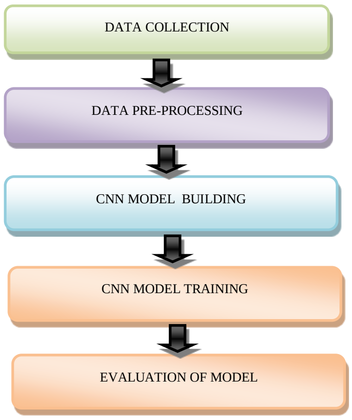

Figure 2: Workflow of our methodology

III. STATISTICAL ANALYSIS

Table 1: Train image data amount

Fruits Name	Amount
Fresh Apple	1693
Fresh Banana	1581
Fresh Orange	1466
Rotten Apple	2342
Rotten Banana	2224
Rotten Orange	1595

Table 2: Test image data amount

Fruits Name	Amount
Fresh Apple	395
Fresh Banana	381
Fresh Orange	388
Rotten Apple	601
Rotten Banana	503
Rotten Orange	403

A. Data Pre-Processing

Data processing is a very important state. Data processing after data collection becomes very important for image classification-related problems. We have divided our data set into eighty percent training and the rest for testing. We gather greater than 10000 picture facts from specific assets and strive to needless or noisy facts. Since we have used RGB images, it is recommended that all of these images have the same size & shape. We used 32×32×3 for this set.

B. Data Organizing

Data Augmentation Over fitting is a common problem when the dataset is limited. As far our dataset is limited we may be get trouble in over fitting. For eliminating over fitting we implement data augmentation. It is actually artificially expanded the dataset. In this segment we divided records and keep them in records folder check and educate, we additionally use right here validation folder for test educate records validation. Then we divided the ones check and educate folder's records in greater folder like fresh apple, rotten apple, fresh banana or rotten banana etc.

C. Proposed Methodology

CNN works with two significant parts first one is feature extraction and next one is classification. Convolutional layers used for feature extraction and fully connected layer used for classification. In our proposed model 4 convolutional layer, 4 pooling layer introduced. At first, CNN takes input images dimension of 32x32x3. For getting better result RGB channel used here. In first convolutional layer filter size of 32 with 3x3 kernel introduced with a ReLU activation function to adding non-linearity. Later a max-pooling size 2x2 used for reduce the dimensionality. Filter size of 64 with 3x3 kernel used again with ReLU activation in second convolutional layer. Later 2x2 max-pooling used. Reduce over fitting again a dropout rate of 0.25 used after forth layer. A flattening layer used for make 2D sequences into 1D matrices. Later a fully connected layer 128 nodes used with ReLU activation. Again dropout rate of 0.25 used for reduce over fitting. Last a dense layer of 6 units used along with a Softmax activation as for classification.

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Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 510, 510, 32)	896
max_pooling2d (MaxPooling2D)	(None, 255, 255, 32)	0
conv2d_1 (Conv2D)	(None, 253, 253, 64)	18496
max_pooling2d_1 (MaxPooling2	(None, 126, 126, 64)	0
dropout (Dropout)	(None, 126, 126, 64)	0
conv2d_2 (Conv2D)	(None, 124, 124, 128)	73856
max_pooling2d_2 (MaxPooling2	(None, 62, 62, 128)	0
dropout_1 (Dropout)	(None, 62, 62, 128)	0
conv2d_3 (Conv2D)	(None, 60, 60, 256)	295168
max_pooling2d_3 (MaxPooling2	(None, 30, 30, 256)	0
dropout_2 (Dropout)	(None, 30, 30, 256)	0
conv2d_4 (Conv2D)	(None, 28, 28, 512)	1180160
max_pooling2d_4 (MaxPooling2	(None, 14, 14, 512)	0
dropout_3 (Dropout)	(None, 14, 14, 512)	0
flatten (Flatten)	(None, 100352)	0
dense (Dense)	(None, 128)	12845184
dropout_4 (Dropout)	(None, 128)	0
dense_1 (Dense)	(None, 128)	16512
dropout_5 (Dropout)	(None, 128)	0
dense_2 (Dense)	(None, 6)	774

Total params: 14,431,046
Trainable params: 14,431,046
Non-trainable params: 0

IV. EXPERIMENTAL RESULTS AND DISCUSSION

A. Experimental Setup

The model trained using Tensor flow 2.0.1. Setting hyper parameters to our model was the first step. Define Batch size as 32. The ratio of our training and testing data as follow 80%, 20%. After that we compiled our model using adam[6] optimizer and our learning rate was 0.0001. Then fit () used for start the training.

B. Performance Evaluation

After finishing training our model got an accuracy of 96.04% with just 10 epoch. Figure 3 which is the accuracy curve of our model where we observed our training accuracy 95.04% and validation accuracy 95.21%.

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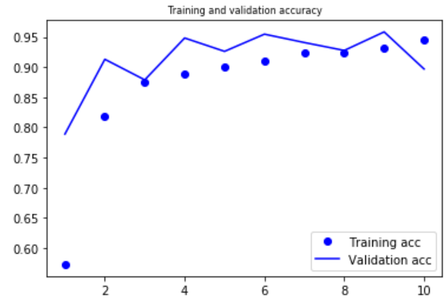

Figure 3: Training vs Validation accuracy

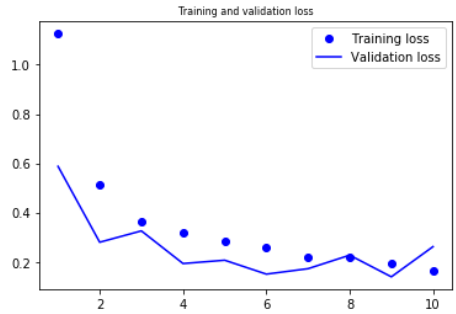

Figure 4: Training vs Validation loss

C.Final Result

Given the input image the model properly classify and grade the given fruit banana as fresh banana . After we are ran our dataset and created the model from the given data, we found the output what we needed. Training and testing stuff, we found that our model performs very well and it can detect fresh & rotten fruits 95% accurately.

```
probs: [[0. 1. 0. 0. 0. 0.]]
class_index: 1
freshbanana
```

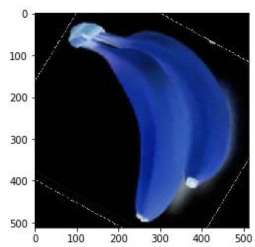

Figure 5: Graded Output

V. CONCLUSION

The sorting of fresh and rotten fruit is of great importance in agriculture. In this paper, a model based on CNN is presented. In this work, the effects of various hyper parameters. i.e. batch size, number of epochs, optimizer, and learning rate are examined. The results prove that the proposed CNN model can clearly classify fresh and rotten fruits and produce them better. Therefore, the proposed CNN model automates the process by which the human brain classifies fresh and rotten fruit using the proposed convolutional neural network model to classify fresh and rotten fruit. Reduce human error during the proposed CNN model achieves an accuracy of 95%.

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e-ISSN: 2250-0758 | p-ISSN: 2394-6962
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