Development of Fruit Classification Models Using Deep Convolutional Neural Network

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Abstract— Classifying fruits from an image is a remarkable research area when we talk about computer vision. In this regard, this paper proposes a system where fruit detection and fruits classification are performed. In India, fruit yield is turned down because of the post conceding of many spots(disease) on the fruits by the farmers at the end. Agronomists struggle a lot for economical loss across the world. We can say that fruits diseases are the main cause of agricultural loss. To improve their productivity, it is important to know the health status of fruits to help the farmers. This motivates us to design and develop a model to help farmers detect the diseases in the early stage itself. The idea behind this work is to develop automatic models that recognize the disease's level and grade them accordingly. Convolutional neural networks opted for the classification, again retrained using the transfer learning technique. The system is developed in the Tensor flow platform. For the proposed work three to four types of fruits have been considered. The model shows 98.17% training accuracy, whereas, the deep learning-based fruits classification test model shows 99.99% accuracy.

I. INTRODUCTION

Classification of fruits has obtained linchpin over the years, it plays a vital role in the agriculture sector such as marketing, production of food, packaging, and education too. Up to the time, agriculture was labor expensive to find skilled labor to increase the production of the crops. Hence producing different crops is the most costly factor. Besides, collecting and classifying forte crops such as Guava, cherry, orange, citrus, apple, and mango are tedious jobs because of their varieties, e.g., if we talk about apples more than 8,000 varieties of such fruits are fattening across the world in detail shown in [1]. As a result, automation helps to mitigate labor costs and increase production. Earlier, researchers have presented many classification approaches to develop the models to defeat the manual recognition of healthy and diseased fruits, which is expensive. In such literature, they have been used color, size, shape, and texture features under classification approaches shown in detail in [2], [3], [4]. As per the paper cited, they have been utilized to acquire the methodology of extraction of features with the combination of classes. Hence developed models are not efficient for all types of fruits and it can be misleading the predictions. Network CNN is a trendy research area now whenever we talk about object detection and image classification kind of work. The utilization of the Convolutional Neural systems is operated by the actuality that they are capable to extract features from provided input images. If we compare to the conventional algorithms for classification, in Convolutional Neural Network the input image can be straight fed into the system, generally, this avoids pre-processing and feature extraction process because in this all these happens by default automatic. Generally, CNN is made up of 3 layers is Convolutional layers, Pooling layers, and Fully Connected layers. Convolutional Neural Network achieved a lot of appreciation while winning the rivalry of ImageNet [5]. Behind time, heterogeneous CNN architecture ventured by famous researchers, we can say that diversely the width and depth of the model layers and got replacing the layers, explore in details [6], [7], [8], [9]. For example, to clarify the Convolutional Neural Network strategy, Max pooling layers got restored by Convo layers with a huge number of strides explained in [7]. There is always a possibility of overfitting while training the automatic models but there is a feasible solution to control the overfitting is Dropout, the conception of drop out the connection of some layer while training the model to explain in detail [10]. How Fully connected layer is replaced by the Global Average Pooling layers shown in [9]. To train our model, we opted for the Kaggle [11] dataset known as fruit-360, which consists of 81 varieties of fruits. In this experiment, we have used GPU to increase efficiency.

II. LITERATURE SURVEY

In recent years image classification using Deep Neural Networks has made significant progress. For pattern recognition, Convolutional Neural Network has been extensively applied for image classification and object detection shown in detail [5], [6], [12]. Authors have shown in [13] how the model got trained utilizes RGB and near-infrared set of images, with the amalgamation of images for better results. CNN building exhibits fruit classifications in orchards including almonds, mangos, and apples shown in detail [14]. Numerous strives have been made to automatically identify fruit status and classify harvesting with robots and farming using the Deep convolutional learning strategy shown in detail [2], [15]. Authors have prospected CNN for fruit automatic detection explore in detail [16], [17]. The authors of [18] explained deeply how the Classic Convolutional Neural Network strategy was used to train and test the same dataset.

III. EXPERIMENTS AND RESULTS

To create CNN-based automatic models, we have been used Keras with the tensor flow library from a python programming language. We opted for the Keras library from TensorFlow because it makes experiments speedy for Deep neural network models. Along with being user-friendly, it is easily operated. it also consists of Neural networks blocks for example layers, activation functions, and optimizers explained in detail [15]. CNN clarifies to start with Input, Convolutional layers, Relu, Strides, and SoftMax. Convolutional models include images in the form of 3-dimensional objects. RGB here declares as the depth of the image which consists of three layers deep since digital color images captured RGB channels have a combination of Red Green Blue. We have given the input image is in the Convo layer. Convo Layer supposes to extract features mapping from linear convolutional filters from input images by using activation functions for example Relu, Sigmoid, tanh, etc. as per the need of the classifiers. After that, all such extracted features must pass through the next layer of CNN, two of them followed by stride 2. As

```
img = image.load_img('/content/drive/MyDrive/COMTECH_FruitC
plt.imshow(img)
```

```
<matplotlib.image.AxesImage at 0x7f44212562d0>
```

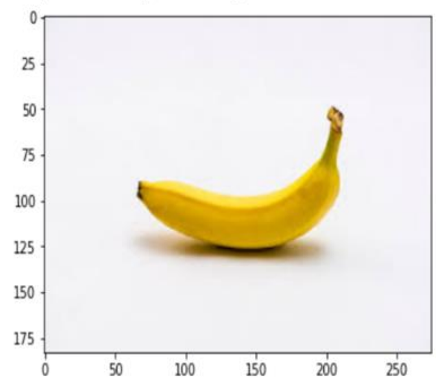

Figure 1: Sample Input Set

```
img = image.load_img('/content/drive/MyDrive/COMTECH_FruitCL
plt.imshow(img)
```

```
<matplotlib.image.AxesImage at 0x7f44211c2cd0>
```

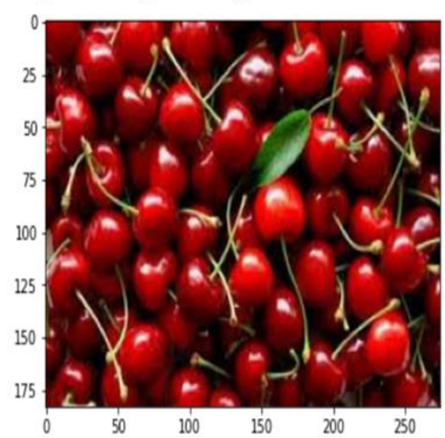

Figure 2: Image sample dataset

the kernel of the Convolutional network is slithering the input, hence this utilizes the stride to regulate where and how many positions need to skip. Stride is the amount by which the filters shift. When we are using stride 2, that indicates 2 positions need to skip. ReLu is the Linear Rectifying Units utilized for hidden layers present in deep neural networks. There are some conditions too such as when Relu shows output 0 when input is lesser than '0' and when the input is larger than

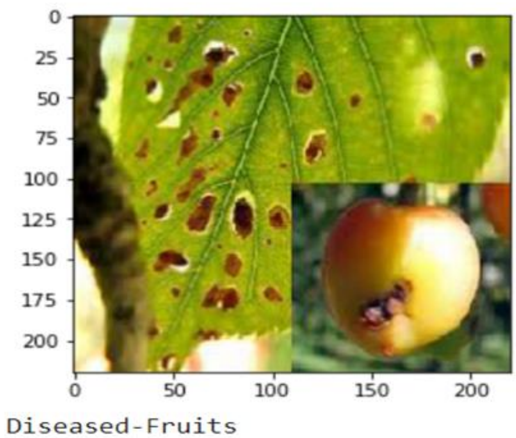

Figure 3 CNN: Models outcome as diseased fruits

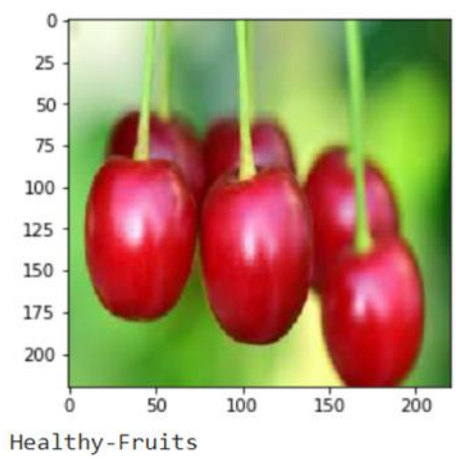

Figure 4: CNN Models Loss rate

'0' the output would be equal to the input which we

Figure 5: CNN outcomes

are providing. So, hence it is not allowed to mitigate the size of the architecture. The resultant utilizing the activation function Relu speedy to train huge models. Global Average Pooling is utilized to mitigate the number of specifications and to secure the developed model from overfitting. The idea behind mitigating the filter size by normally having an average of the entire features first presented by [13]. Initially, a bundle of 128 images set with the same input size has proceeded via a Convo layer of 24 filters of size 3 × 3. For reduction of dimension, the Convo layer followed with Stride 2 Implemented in layers 2, after passing the input within the same series layer by layer, layers contain 48 kernels of size 3×3 and the output of SoftMax is equal to the total number of fruit classes need to classify. Hence the output of the previous layer is treated as an input for the next layer. passed into

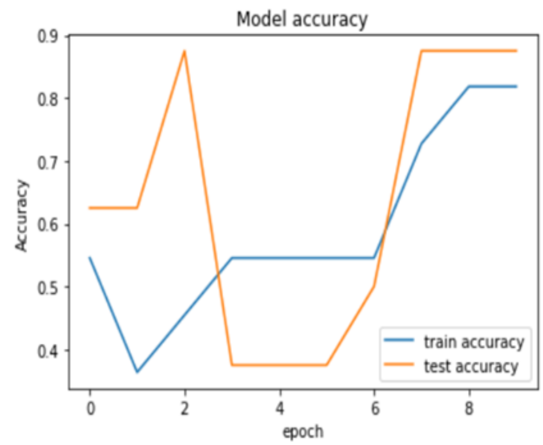

Figure 6: CNN Models Accuracy rate

another convolutional layer that has 96 kernels of size 3 × 3 for better model clarifications, The purpose of mitigating the filter size from 3 × 3 to 1 × 1 is explained in detail [13]. We have implemented 10 epochs for getting the good results of the models. During testing, we opted for some simple images from the internet also. And we got good accuracy as the elevated score for prediction of the category of fruit as shown in detail [18]. Convolutional Neural Network consists of many convo layers, out of which are 3 max-pooling layers for reduction of dimension including stride 2. To avoid, Dropout layers are included in the model explained in detail [10]. Dataset fruit-360 consists of 81 classes, and in which each has a heterogeneous category of a variety of fruits and is broken into 2 parts; the training set contains 31300 images, the validation set has 5740 images, a total number of images in the dataset is 37140. From 81 classes of fruits, only one image was acquired from each category shown in figure 1 and figure 2. Figure 1 and figure 2 show the input dataset for the model training. The size of each image is set as 200 × 200 pixels. For testing the model, we have opted for some other images also those are out of fruit-360 datasets.

Figure 4 shows the accuracy rate of the CNN model in the form of a line graph and figure 5 shows the loss results of the developed model. Figure 6 shows that the classification results as a healthy fruit. figure 3 depicts classification results as diseased fruits. In these experiments, we have taken epoch values as epoch = 10 (initially) using CNN-Inception V3 results are explained in detail [26], then we checked with epoch value = 50 also for better accuracy of the developed model as shown in figure 6. In the cited paper, Table 2 shows the results in the form of accuracy and loss for all three developed models. In [27] we have performed weed and cowpea leaves classification using novel VGG16 architecture models and performance in the form of accuracy was good concerning the standard vgg16 convolutional neural network and we are citing that vgg16 papers also here for a better understanding.

IV. CONCLUSION AND FUTURE SCOPE

We presented a novel methodology to classify healthy and diseased fruits based on image classification using a Convolutional Neural Network. We have found that CNN- Sequential model gives good accuracy along with supreme performance, and defeats overfitting problems. furthermore, we estimated the results of classification as the accuracy on the fruit dataset which consists of 4 categories of images of fruit. The model shows 98.17% training accuracy, whereas, the deep learning-based fruits classification test model shows 99.99% accuracy using CNN-Sequential. Convolutional Neural Network flourishing trained the model to classify heterogeneous images of fruits.

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