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FRUIT DISEASE CATEGORISATION BASED ON CONVOLUTIONAL NEURAL NETWORKS

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Abstract

Applications of artificial intelligence have become very relevant in all sectors. This is especially true in agriculture, where it is used to protect crops from disease and to take appropriate measures to control the disease at an early stage. In this study, a model is used that employs deep learning techniques to classify fruits into different types: diseased and healthy. This involves the development of a Convolutional Neural Network (CNN) model to classify fruits into diseased and healthy in two different classes, considering each fruit individually for three different fruits. It was found that the deep learning model used in this research work has higher accuracy when compared with other existing models considering the same data set. The proposed deep learning model was compared with different pre-trained models LeNet5 and AlexNet trained on the same dataset. It was found that the proposed CNN model achieved over 95% accuracy for each of the fruits for different classes. Moreover, the developed CNN model achieved higher accuracy than other existing models, indicating the usefulness of CNNs for fruit disease classification with high accuracy.

Keywords: *Agriculture, Convolutional Neural Network, Deep Learning, Fruit disease detection, AlexNet, LeNet5*.

I. Introduction

The CNN model considers an image as input and assigns weights to different fragments of an image that allow the CNN model to distinguish between different images. These weights allow the CNN to behave like biological neurons in the human brain. The architectural aspects of the CNN model were inspired by the biological neurons in the visual cortex of the human brain. The individual units respond to stimuli in a small portion of the visual field called the receptive field. A series of total fields are stacked on top of each other so that they all together form a total visual field. The advantage of CNN is that the preprocessing required for it is much less than for other machine learning methods. The biological units in the human brain can respond to the stimuli from the visual field, which are called receptive fields. In principle, a visual field can be formed from different layers of fields. For this reason, the pre-processing effort is lower compared to other machine learning classification methods. This is one of the reasons why many of the applications that use images as input to the model make CNN the perfect choice for classification tasks.

Agriculture is dominant in many countries around the globe, and people in these countries depend on agriculture for their livelihood. In agriculture, it has been observed that many fruits are affected by diseases and are therefore wasted [1]. It was found that almost 40% of fruit crops are affected by the disease, which causes great problems for farmers [2].

Therefore, early detection of the disease is of great importance, which in turn makes it easier for farmers to take precautionary measures so that fruit crops are not affected by the disease. Developing countries like India are going through a technological age, and it is no surprise that even the most remote villages in the country have Internet access and facilities. The deep learning model could help farmers identify the disease that is affecting their crops. The main motive of this research is to detect the disease at an early stage, which helps the farmer to detect the infection early and take countermeasures. Another advantage is that even if the farmer detects the disease at a later stage after it has spread, he can take corrective measures to prevent the spread of the disease to other plants in the crop, leading to an improvement in fruit production around the world.

II. Earlier works done

The earlier researchers have worked intensively on the detection of fruit diseases. Some recent research conducted by earlier researchers is listed in this section. Various methods have been proposed for fruit disease identification using K-Means clustering, ANN and SVM techniques. They considered the phenotypic characteristics of the fruit as input and predicted the disease. They found that SVM provides good accuracy in predicting the disease compared to other methods [3]. Raju Hosakoti et al. developed a CNN model for fruit disease detection using CNN for feature extraction and classification [4]. Ashok Kumar Saini, Roheet Bhatnagar and Deveshkumar Srivatsava have developed various models: InceptionV3, ResNet50, VGG16, and VGG19 with deep convolutional neural networks using transfer learning. They found that VGG19 achieved 99.89% accuracy in predicting disease using transfer learning than the rest of the other models [5]. Sharada P. Mohanty et al. developed a CNN model for the detection of 14 plant categories and 26 diseases. They found that the CNN model achieved 99.35% accuracy in predicting the disease in a test dataset consisting of 54,306 images of infested and non-infested plant leaves [6]. Poonam Dhiman et al. proposed a deeplearning model to detect targeted areas of disease in fruit with four intensity levels. These are high, medium, low and healthy. For this purpose, a transfer learning model using VGGNeT was considered. The model provided a prediction accuracy of 99% for low severity, 98% for high severity, 96% for healthy, and finally 97% for medium severity detection. It was found that the proposed model efficiently and accurately detects the disease [7]. Z. M. Khaing et al. proposed a hybrid network using a contour-based approach to classify fruits and their diseases. They proposed a deep learning model VGG19 trained with a plant dataset from which key features were extracted. The contour features are filtered out using the pyramid histogram of the oriented gradient and fused with deep features using a series- based approach. The proposed method achieved 99.6% accuracy compared to other existing methods [8]. Bhavya K. and Pravinth Raja presented an innovative method to discriminate the variety of apples considering fruit quality. They used principal component analysis to extract the features and developed four different models, K-NN, LSVM, KSVM and decision tree to categorize the fruits according to quality parameters. They found that SVM and decision tree models performed well compared to the existing techniques [9].

III. Methodology

The dataset used to train the model was from the Kaggle dataset. Before feeding the data into the CNN model, techniques were applied to preprocess the data. The dataset consisted of 3 fruits with six classes. We used 1600 images for fresh fruit and 1600 images for rotten fruit to train the model, and 391 images for fresh fruit and 450 images for rotten fruit were considered to test the images individually for all three fruits. Table 1 below shows the composition of the images in the database and the number of images in each class that were considered for the proposed research during the training and testing phase.

Type / Fruits for training	Apple	Banana	Orange
Fresh	1693	1581	1466
Rotten	2342	2224	1590

Table 1: Training Phase: Total number of fruits considered for training.

Type / Fruits for training	Apple	Banana	Orange
Fresh	395	381	388
Rotten	601	530	403

Table 2: Testing Phase: Total number of fruits considered for testing

A. Dataset Augmentation

The Image Datagenerator Function was used to process the images and various techniques such as rescaling, zoom_range, sheer_range and horizontal flip were applied to the training data. The test dataset includes 996 images of apples, 911 images of bananas and 791 images of oranges to test the proposed model and no other filters were applied. The entire image database was set to 32*32 pixels before being used as input to the CNN model.

B. Tools and Libraries used

We used different tools such as Jupiter Lab, Google Colab to create the classifiers. Python3 and its libraries TensorFlow, Keras, Scikit-learn, Pandas, Numpy, Mat- plotlib and Seaborn were used for various tasks. The CNN model was trained and tested on a laptop with Windows operating system.

C. Proposed Model

In the current research, the researchers developed a deep learning model that was trained with different datasets. This dataset includes three different fruits, namely apple, mango, and banana. The CNN model was used as a classifier to validate the input image. The model classifies an input image as rotten or fresh depending on the type of fruit given as input to the classifier. If the input image is a fresh fruit, the model predicts that it is a fresh fruit, and if the input image is a rotten fruit, it classifies it as a rotten fruit. Finally, the result is known to the end user. Figure 2 below shows the architecture and flow structure of the model for classifying the input image into two different classes.

D. Implementation

The proposed CNN model can help farmers detect fruit diseases at an early stage so that the entire fruit crop is not affected by the disease. Based on an image of different fruits, the proposed model classifies an instance as healthy or diseased.

E. CNN Architecture and Training

The proposed CNN architecture was used to train and test the models with different datasets. The proposed CNN architecture consists of 23 layers, of which 6 are convolutional layers and 3 are maxpooling layers. The fully connected layers are 2 in number. The first convolutional layer has 32 neurons and is connected to another convolutional layer with 32 neurons. Batch normalization technique was used between the layers. This technique was used to speed up the training set and achieve higher learning rates, making the model easier to learn. This convolutional layer is connected to another maxpooling layer with 16 neurons, and again the batch normalization technique was used. This maxpooling layer is again connected to a convolutional layer with 16 neurons, and a dropout technique was used between the layers. This convolutional layer with 16 neurons is again connected to another convolutional layer with 16 neurons, and again a batch normalization technique is used. This convolutional layer with 16 neurons is connected to a max-pooling layer with 8 neurons, and again a batch normalization technique was used. This max-pooling layer is connected to another convolutional layer with 8 neurons, and this in turn is connected to another max-pooling layer with 4 neurons. This max-pooling layer is connected to a apartment layer and then to a dense layer. The activation function ReLu was used for all intermediate layers. The input to the CNN model is an image of size 32*32. The padding technique was used for an image given as input to the model and for none of the layers of the network. The last layer is an output layer consisting of 6 units with softmax activation function. The proposed model was developed with the aim of classifying the dataset with binary classification. At least 20 epochs were applied to the proposed model. The proposed CNN model was trained using a supervised learning algorithm, and feature extraction was performed using the training dataset; validation was performed using the test dataset. Data uploading was done using Google Colab, which allows any image to be used as input to the model. The image is processed, classified and the output is shown in the figure as diseased or non-diseased fruit.

IV. Results and Discussion

The proposed CNN model has disease detection architecture for three fruits - apple, orange, and banana. The performance of the proposed CNN model was compared with different models such as Alexnet and LeNet-5. The graph below shows the accuracy of the proposed CNN model (adapted) in terms of epoch and accuracy. From the following figure (1), it can be seen that the accuracy of the model increases as the number of epoch increases.

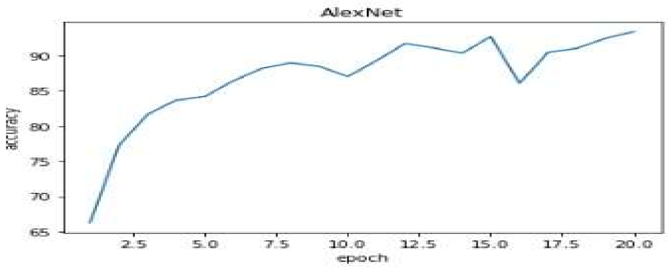


Fig 1: Performance of AlexNet w.r.t epoch and accuracy

```
Model: "sequential_10"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_27 (Conv2D)          (None, 32, 32, 32)        896

 batch_normalization_23 (Bat  (None, 32, 32, 32)       128
 chNormalization)

 conv2d_28 (Conv2D)          (None, 32, 32, 32)        9248

 batch_normalization_24 (Bat  (None, 32, 32, 32)       128
 chNormalization)

 max_pooling2d_17 (MaxPoolin  (None, 16, 16, 32)       0
 g2D)

 dropout_8 (Dropout)         (None, 16, 16, 32)        0

 conv2d_29 (Conv2D)          (None, 16, 16, 64)        18496

 batch_normalization_25 (Bat  (None, 16, 16, 64)       256
 chNormalization)

 conv2d_30 (Conv2D)          (None, 16, 16, 64)        36928

 batch_normalization_26 (Bat  (None, 16, 16, 64)       256
 chNormalization)

 max_pooling2d_18 (MaxPoolin  (None, 8, 8, 64)         0
 g2D)

 dropout_9 (Dropout)         (None, 8, 8, 64)          0

 conv2d_31 (Conv2D)          (None, 8, 8, 128)         73856

 batch_normalization_27 (Bat  (None, 8, 8, 128)        512
 chNormalization)

 conv2d_32 (Conv2D)          (None, 8, 8, 128)         147584

 batch_normalization_28 (Bat  (None, 8, 8, 128)        512
 chNormalization)

 max_pooling2d_19 (MaxPoolin  (None, 4, 4, 128)        0
 g2D)

 dropout_10 (Dropout)        (None, 4, 4, 128)         0

 flatten_4 (Flatten)         (None, 2048)              0

 dense_12 (Dense)            (None, 512)               1049088

 batch_normalization_29 (Bat  (None, 512)              2048
 chNormalization)

 dropout_11 (Dropout)        (None, 512)               0

 dense_13 (Dense)            (None, 6)                 3078

=================================================================
Total params: 1,343,014
Trainable params: 1,341,094
Non-trainable params: 1,920
_________________________________________________________________
```

Fig 2: The proposed architecture of the CNN model till the last dense layer is given above.

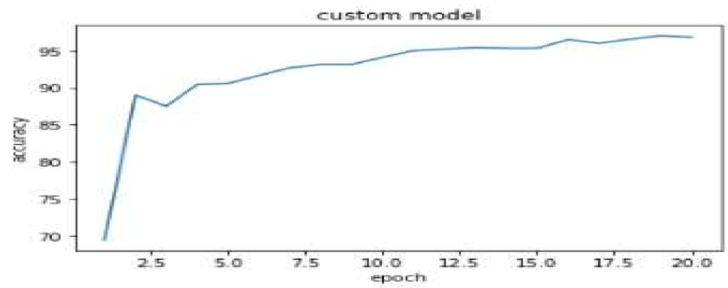
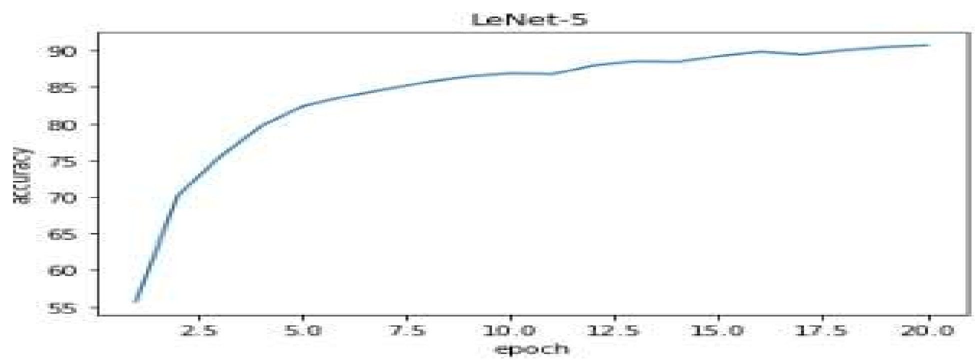
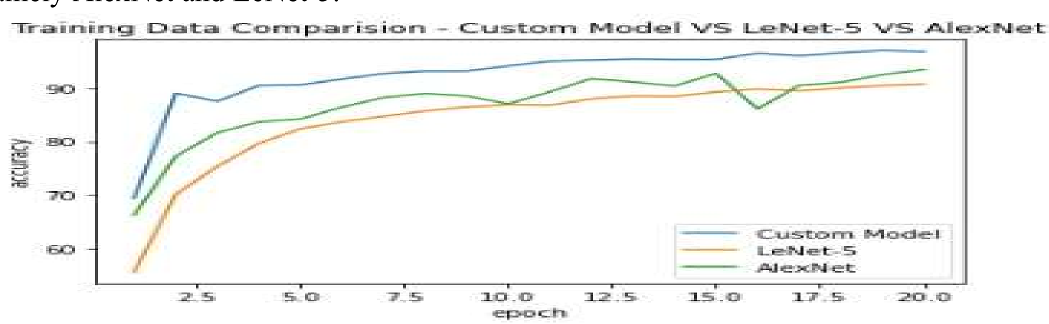


Fig 3: Training accuracy of the model AlexNet epochs on X-axis and accuracy on y-axis.

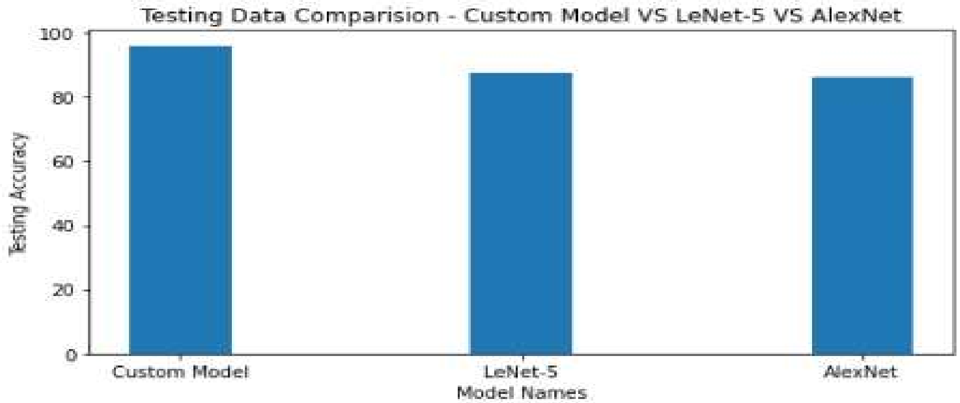
Similarly, the proposed adapted CNN model was also compared with the LeNet-5 model, and the figure below shows the accuracy of the LeNet-5 model during the training phase. It can be observed that the accuracy of the LeNet-5 model increases as the number of epochs increases.



The performance of all models, i.e., the proposed CNN model, the Alexnet model, and the LeNet-5 model, during the training phase is shown below. From the figure, it can be seen that the performance of the fitted model during the training phase is better than the other models, namely AlexNet and LeNet-5.



The test accuracy of the model from the figure below also shows that the proposed adapted CNN model outperforms the other existing models well.



V. Conclusion and Future Scope

In the current study, different CNN models are presented to classify the three fruits individually into diseased and healthy classes. The proposed models achieved over 95% accuracy for each of the three fruits studied. As an extension of this research, we would like to develop a model based on an Android app that can be used by novice users to detect fruit diseases more easily and quickly, so that farmers can use it to detect fruit disease immediately. As a result, farmers can not only save their crops, but also take appropriate measures to contain the spread of the disease to other plants. Moreover, the farmer can save other plants in the neighbourhood of the diseased plant, provided that the disease is detected early. The accuracy of the proposed model can be increased arbitrarily if the data set consists of many fruits with different types of diseases. Similarly, different stages of a particular disease can be detected if there is a large data set with different fruits..

VI. References

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