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# A CNN BASED APPROACH TO IDENTIFY NOVEL DISEASES IN PLANTS

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**Abstract:**

The most recent development in the field of farming is utilizing Machine Learning and Deep Learning methods to identify its problems. Deep convolutional neural networks are very effective in this field to identify and classify the diseases that are affecting the crop. ResNet-50 is a layered network which uses computer vision as input to organize the model. We trained it using the Plant Village dataset which contains over 54000 images in 38 different classes of species and diseases. The CNN with five layered structures maintained 95.6% accuracy and the classification model was shown to be very effective on the testing data.

## Introduction

Artificial intelligence is founded on the idea that human intelligence may be described in such a way that a computer can simply imitate it and carry out tasks ranging from simple to sophisticated. Artificial intelligence aims to improve learning, reasoning, and perception.

Agriculture and farming are two of the world's oldest and most essential occupations. It has a significant impact on the economy. Agriculture is a $5 trillion industry around the world.

By 2050, the worldwide populace is anticipated to contact in excess of nine billion individuals, requiring a 70% increment in agricultural creation to satisfy need. As the total populace develops, land, water, and assets become inadequate to keep the interest store network going. Therefore, we need to adopt a more essential strategy and become more proficient in how we farm so that we can be more productive.

The global population has already surpassed 7.5 billion people in 2017, and it is expected to reach 9.7 billion by 2050. The need for food is increasing as the world's population grows. Agriculture is one of the most frequent jobs in India. Experts estimate that roughly 20% of India's population works in agriculture-related employment, yet agricultural products make for only 8-10% of Thailand's gross domestic product (GDP). We are certain that technology can be integrated into agriculture to improve agricultural production efficiency and crop yields.

In this paper we build an overall model for all the plants and diseases available and maintain the accuracy of the model. The data from the publicly available website from plantvillage.org is used. We give the input images to the CNN network and it automatically identifies the disease, we build the architecture of it as light as possible to implement it in real time devices like mobile phones with simple applications as they have limited computational power.

Efforts to build automated methods for detecting plant illnesses using visual symptoms on leaves have exploded due to the advent of computer vision models. These methods attempt to make farmer participation as simple as feasible while also making the discovery system as idiot proof as could be expected. Preceding the inescapable accessibility of profound learning models, specialists generally depended on picture handling/include extraction to make sickness conclusion calculations, with conflicting outcomes. The most difficult part of this technique, characterizing manifestations for PC acknowledgment, has been overwhelmed by using profound learning, in which the models don't should be indicated and rather become familiar with the attributes through streamlining. In recent years, a lot of research has successfully used deep learning models to achieve varying degrees of accuracy on laboratory/field pictures. When evaluated on data that is identical to that used during training, these accurate classifiers accomplish high exactness, however when tried on various information, they flop appallingly. For

instance, Mohanti[11] and Ferentinos [19] found that preparation models accomplished exactness and certainty in excess of close to 100%, however

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certainty dove to under 40% when thought about in contrast to pictures from dependable web assets. Barbado [15] illustrated various elements affecting the exhibition of profound learning models applied to plant leaf sickness identification and inferred that, in spite of the great achievement pace of created frameworks, including their own, there are various reasons why it is still a long way from being a conventional instrument that could be utilized in genuine world situations.

Following this section are the related work, methodology and results. In the final section, we give some concluding remarks.

## RELATED WORK:

The Plant Village dataset, which involves pictures with negligible inconstancy and steady foundations, has been utilized to prepare and assess most profound learning endeavors for disease ID. Barbado [26] has taken a gander at the presentation of profound learning models prepared on singular injuries and spots, using picture division and augmentation to extend the dataset from few pictures. They tracked down that the models' presentation expanded (12% all things considered) in each plant species contemplated, with exactnesses routinely surpassing 75% in the most confounded occurrence with ten ailments. The picture datasets are fragmented to utilize the most data about the ailment indications by removing distressed segments of the leaves as opposed to whole leaf pictures in this examination. By inspecting the self-characterization certainty for every disease type and measuring the results of the two models, it is exhibited that we can prepare with more important information and acquire incredibly great outcomes even in certifiable settings.

Given the unobtrusive number of datasets at present available, move learning, or changing the last yield of a prepared neural organization to a preparation information, has been a noticeable strategy of decision for scholastics (a huge number of pictures when contrasted with a great many pictures needed for preparing models without any preparation). Darmeş et al. [21], Zheng el af. [22], To pt bl. [23], Suryavathi el bl. [24], and Zheng el af. [25] are instances of using this methodology with

pictures from freely accessible information bases, for example, Plant Village [20]

## WORKING

All the models are loaded and the condition if the model is not present is handled by downloading the model from TensorFlow Plant Village is automated in the script. To evaluate the model, we used a part of the huge dataset containing 100 images. It's validation values i.e., bounding boxes of the leaf in the image are stored in a CSV file.
The image is read using OpenCV and it is converted into the tensor data type.

We previously built a CNN model ([18]) that has an accuracy of more than 93 percent for 15 distinct plant species. This research will go deeper into the model. Figure 1 depicts the CNN model used in this investigation. Following the reading of the pictures, noise, distortion, flip, and rotation transformations are performed to 256x256 pixel irregular parts of the pictures. Numerous convolution and pooling stages are applied by changing step lengths (dividing stretch for putting the channels/veils) and cover measurements. Pooling is the way toward applying a veil to every pixel and afterward picking a solitary incentive (for instance, most extreme) from the cover. Multiple convolution and pooling processes are included in the mixing steps in Fig. 1. An enhancer is made to prepare the model loads by taking care of the outcome into a SoftMax work. The model can consequently become familiar with the choice limits important to characterize pictures into one of two classes by adding non-linearities utilizing a Rectified Linear Unit (ReLU) and irregular dropouts during learning. The size of the channels and yields changes as the information goes through the organization (decreasing as it goes through), taking into account preparing and recognition of similar qualities with shifting scaling. Since convolution channels were applied to the entire picture for preparing information, the CNNs are harsh toward include changes like pivot and interpretation. Besides, the pooling layers effectively make the CNNs highlight bending open minded

## Results & Discussions:

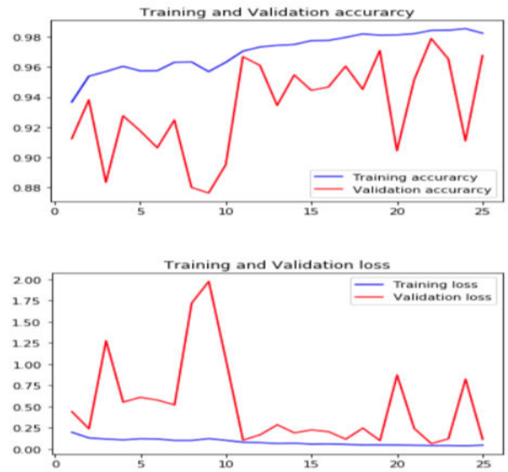


**Fig 1. Training and Validation Accuracy, Training and Validation loss.**


**Fig 2.Identification of diseased leaves.**

```
In [16]:
print("[INFO] Calculating model accuracy")
scores = model.evaluate(x_test, y_test)
print(f"Test Accuracy: {scores[1]*100}")

[INFO] Calculating model accuracy
591/591 [==============================] - 2s 3ms/step
Test Accuracy: 96.77383080755192
```

Save model using Pickle

```
In [17]:
# save the model to disk
print("[INFO] Saving model...")
pickle.dump(model,open('cnn_model.pkl', 'wb'))

[INFO] Saving model...
```

**Fig 3.Overall Accuracy and Model.**


**Fig 4.Prediction of disease on Sample Image.**

## CONCLUSION

When applied to previously unseen real-world pictures, most deep learning algorithms for automated illness diagnosis perform poorly. We show in this study that segmented and annotated pictures may be used to prepare a convolutional neural organization (CNN) model instead of complete images. Model execution on free information ascends from 42.3 percent to 98.6 percent when a similar CNN model is prepared utilizing sectioned pictures (S-CNN) as opposed to full pictures (F-CNN). What's more, a quantitative investigation of self-characterization certainty uncovered an impressive improvement, with 82% of the test dataset exhibiting an expansion in certainty. Pre-processing pictures before model training in CNN may become increasingly important as richer datasets become accessible in the future. This can help achieve high real-world performance.

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