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Empowering Indian Farmers: Deep Learning for Early Plant Disease Prediction

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Abstract— *As the foundation of the Indian economy, the agriculture sector provides a living for many people in the nation. Maintaining crop productivity and quality is therefore essential. However, managing agricultural diseases and detecting them are very challenging activities requiring a large investment of time and skilled staff. This work intends to cover the road for the early prediction of plant diseases using deep transfer learning techniques. Through simplification of early involvement measures, this technique seeks to lower financial losses. The recommended application predicted plant leaf diseases with an accuracy percentage of 98.62%.*

Index Terms— *Deep Transfer Learning, CNN, ResNet50, VGG16, Inception V3, Plant Diseases*

I. INTRODUCTION

Essential needs of humans as well as animals like food, shields, building materials, ayurveda medicines, fuels, wood, etc. are fulfilled by the plants and also minimize air pollution. The environment should be protected by humans from problems caused by floods, fire, human development, etc. The cultivation of plants is important as it gives us different types of fruits, vegetables, grains, nuts, and medicines. We need wood for construction purposes, furniture, paper-making, etc. Bio-fuel production can be done by the decaying of the plant as it forms the fertilizer, also used for generating electricity. Losses in crop yield is one of the difficulties in agriculture. It affects the economy of the country. Because of plant diseases the quality and also the quantity are being affected.

There are many diseases in agricultural plants, if we can control them then we will control the production of wastage. Many different methods are there to check diseases are as man-based and technology-based checking. Plant diseases like pathogens, microorganisms that are living, bacterial problems, fungi-infected plants, nematodes, and viruses-affected problems in plants cannot be easily detected by human eyes. We should use some technology. With the help of image processing and machine learning techniques, we will try to predict plant disease. The research objective is to develop a technology in the agricultural field, based on deep transfer learning techniques to detect plant disease.

II. RELATED WORK

Balwant J Gorad et al. (2019) give a better disease prediction system for the brinjal plant. The data that is provided by the farmers, is split by k-means cluster. Farmers collect images from their phones, tablets, cameras, and other sources that are forwarded to the system and then the system creates a dataset from that periodically it is done and hence plant diseases are predicted by the system.[1]

R. Neela et al. (2019) proposed a model to classify tree leaves, identify diseases, and also suggest fertilizer using SVM and CNN. The data they used was collected by themselves. They compared SVM and CNN and got the result that SVM is more efficient than CNN for their model.[2]

Samhitha Suda et al. (2020) used CNN to detect diseases of plants in medical as well as agriculture. The system with 98% accuracy not only detects the disease but also suggests providing remedies. With the help of this model, we can take the help of drones to monitor crops for any disease with the installation of a model on drones.[3]

Pranesh Kulkarni et al. (2021) used a public dataset for the research in which healthy and unhealthy images of different crop plants were included. They used a Random Forest Classifier. They got 93% accuracy through the system they developed.[4]

Arvind Kumar Shukla et al. (2021) proposed a system with different classifiers like k-mean, CNN, and SVM. With CNN the accuracy rate was 83.80%. With the help of image processing potato plant diseases were classified. It is obtained from the research that a large amount of data can be easily trained and tested.[5]

Houda Orchi et al. (2021) performed a contemporary survey on the detection of crop diseases using artificial intelligence and the Internet of Things. They took the research work done with crops like rice, cotton, citrus, tomato, maize, wheat, and watermelon with several methodologies adopted by researchers like IoT, transfer learning, machine learning, image processing, deep learning, and transfer learning. For segmenting diseased leaves and classifying crop diseases widely k-means algorithms were used.[6]

Pallepati Vasavi et al. (2022) present a comprehensive overview of the recent research in the agriculture field which uses machine learning, deep learning, or image processing techniques. They discussed performance measures used and described limitations and future work requirements.[7]

Mohammed Hussein et al. (2024) developed the model based on CNN and used a dataset from PlantVillage. The images are of tomato plants. According to the researchers, their CNN model is more efficient than any other CNN model. Here they used less (4) layers and 40 epochs to get an accuracy of 96%. The proposed model will not use storage as much as the traditional CNN model.[8]

Anita S. Kini et al. (2024) did the research work with image processing on black pepper leaf. The images they used were real-time images. Researchers used ResNet18, GoogleNet, SqueezeNet, and InceptionV3 model to predict the plant disease. The highest accuracy they got is 99.67% with the proposed ResNet18 model.[9]

Atul B. Kathole et al. (2024) presented the model with IoT and machine learning where real-time monitoring will be done and with the help of images, the plant disease will be predicted and then alerts will be made to the farmers and also the model will give the much-needed information about further process.[10]

Munaf Mudheher et al. (2024) presented the model with MobileNet and CNN to predict plant disease with the help of image processing. The dataset they used is available on Kaggle for free. The accuracy rates for both the models MobileNet and CNN are respectively 96% and 89%.[11]

Rehyan Dzaki et al. (2024) conducted a comparison between models CNN, VGG16, K-means Clustering, and SVM to detect and predict rice plant diseases. They got the highest accuracy with the VGG16 model. They used a dataset of 120 images named Rice Leaf Disease Dataset.[12]

III. RESEARCH OBJECTIVE

In the field of agriculture, many researchers have done research using machine-learning techniques. A wide range of crops is used in the research work. Tomato is also a widely used crop, hence any research work that will increase the tomato crop quality and quantity will be beneficial for the farmers. If the model predicts the plant disease early then the crop cost will be less. With the help of machine learning, we have tried to predict the plant disease as early as possible. Farmers will be told about the correct fertilizers to be used. Tomato crop yield will be increased. If the crop is sufficient for the human, then the cost will never be high. Hence, we have done research with the tomato dataset and machine-learning techniques. We have done another agricultural research.

IV. PROPOSED MODEL

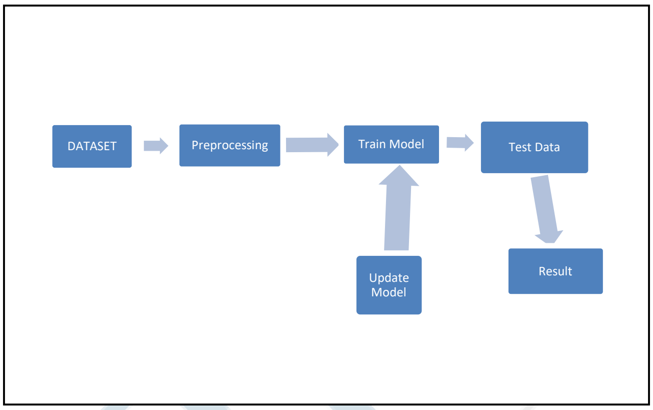


Figure 1: Proposed Model

Image Dataset

To collect the data in digital format (like .bmp, .jpg, .png, .gif) for further processing is image acquisition. Images can be collected from different devices like phones, cameras, tablets, laptops, etc. In this research work, we used a tomato leaf dataset obtained from Kaggle and it is already augmented having 22970 images, 18385 for training, and 4585 for testing. Each class has 10 classes with the same name as diseases like bacterial spot, early blight, late blight, leaf mold, and the healthy also. With the help of Python tools and machine learning techniques, the dataset is pre-processed.

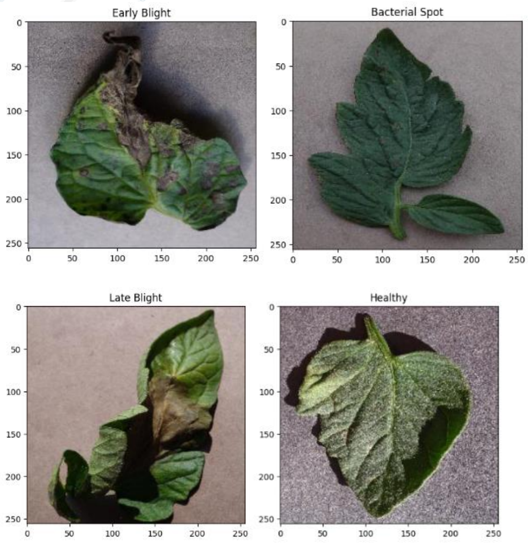


Figure 2: Unhealthy leaves images from the dataset

VGG16

VGG16, a convolutional neural network architecture, is structured with 16 layers of weights, featuring 13 convolutional layers and 3 fully connected layers. It stands out for its straightforward and consistent design approach. The key characteristic of VGG16 is its use of small 3x3 convolutional filters stacked multiple times, which helps in learning hierarchical features from images. VGG16 has been widely used as a pre-trained model for various computer vision tasks, including image classification, object detection, and image segmentation. By leveraging the pre-trained weights of VGG16 and fine-tuning them on specific datasets, it is possible to achieve good performance on a wide range of visual recognition tasks.

Inception V3

Inception v3 is a deep-learning model known for its efficiency and accuracy in image classification tasks. It incorporates the idea of using multiple filter sizes (1x1, 3x3, 5x5) within the same layer to capture features at different scales, enabling the network to learn more diverse and effective representations.

Inception v3 has achieved notable performance on various image classification benchmarks, such as the ImageNet Large Scale Visual Recognition Challenge (ILSVRC). Like VGG16, Inception v3 has also been popular as a pre-trained model, allowing transfer learning for various computer vision tasks. It has also been used in applications such as object detection and image segmentation.

ResNet 50

ResNet50 is a widely used CNN architecture. It is part of the ResNet (Residual Network) family of models and has 50 layers, hence the name "ResNet50."

ResNet50 is known for its deep structure and the innovative use of residual connections, which address the problem of vanishing gradients in deep networks. The residual connections allow the network to learn residual mappings, making it easier to train very deep architectures.

ResNet50 has been popular as a pre-trained model, enabling transfer learning for different visual recognition tasks. It is used in computer vision tasks like image processing, object detection, and image segmentation.

These are just a few examples of CNN architectures, each with its unique characteristics and benefits. Depending on the specific task and requirements, choosing the right architecture can significantly impact the performance and efficiency of your model. For the comparative research, we used a dataset of tomato healthy and diseased images already augmented. While working with an augmented dataset we followed the following steps to train our model

Split the Dataset

Divided our augmented dataset into training, validation, and testing subsets. The training set is used to train the model, the validation set is used for tuning hyperparameters and monitoring performance, and the testing set is used to evaluate the final model's performance. 80% data was used to train the model and 20% for the testing.

Preprocess the Data

Resize the images into 224*224 for the VGG16, Inception V3, and ResNet50 models.

Model Training

Define the hyperparameters for training like batch size 32 and epoch were different for each model.

Evaluation

Evaluate the trained model on the testing dataset to assess its performance and generalization ability. Calculate metrics such as accuracy, precision, recall, or F1 score to measure the model's effectiveness.

$$\text{Accuracy} = (TP + TN) / (TP + FP + TN + FN)$$

Accuracy measures the overall correctness of the predictions. It represents the proportion of accurately predicted samples relative to the total sample size.

$$\text{Precision} = TP / (TP + FP)$$

Precision measures the accuracy of positive predictions by measuring the ratio of correctly predicted positive samples to the total predicted positives.

$$\text{Recall} = TP / (TP + FN)$$

Recall measures the proportion of correctly predicted positive samples out of the total actual positive samples. It focuses on the ability to identify positive samples.

$$\text{F1 Score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall})$$

The F1 score combines precision and recalls into a single metric, where a higher value indicates better overall performance

Where:

TP (True Positives): The number of samples correctly predicted as positive.
TN (True Negatives): The number of samples correctly predicted as negative.
FP (False Positives): The number of samples incorrectly predicted as positive.
FN (False Negatives): The number of samples incorrectly predicted as negative.

V. RESULTS AND DISCUSSIONS

Three deep-learning models for the detection of plant diseases were the focus of this investigation. The highest test accuracy score was achieved by ResNet50, which was trained for 50 epochs. This shows that ResNet50's design is appropriate for identifying plant sicknesses from crop images. The dataset used was obtained from Kaggle and is openly available on the web. Python coding was carried out on Google Colab. Pushing ahead, we mean to upgrade results, extend the dataset, and tackle more complicated illness location challenges in future exploration attempts.

Table 1.- Accuracy, Precision, Recall and f1 Score by Different Model

S. No.	Model	Accuracy	Precision	Recall	F1score
1.	VGG16	0.9575	0.977	0.977	0.976
2.	Inception V3	0.8955	0.945	0.945	0.941
3.	ResNet50	0.9862	0.992	0.992	0.991

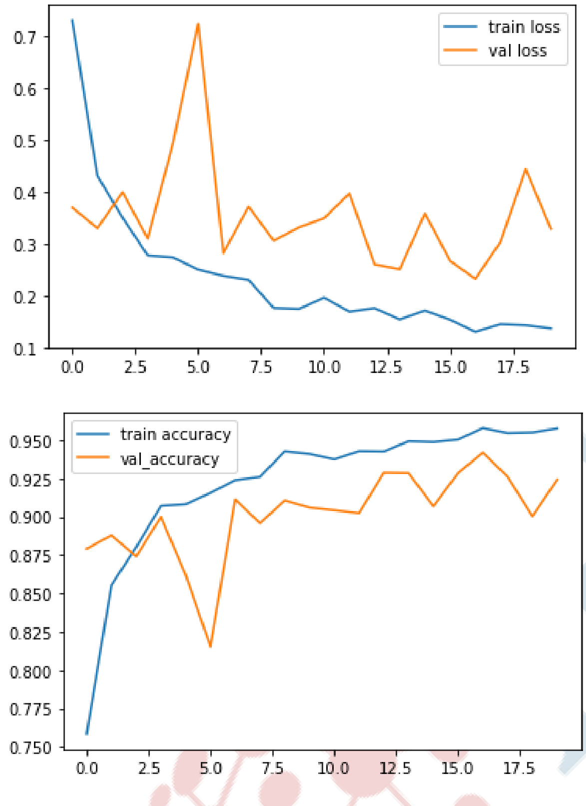
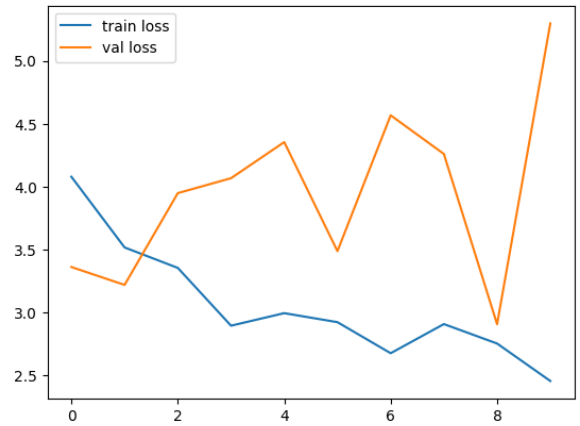


Figure 3: VGG16 Model



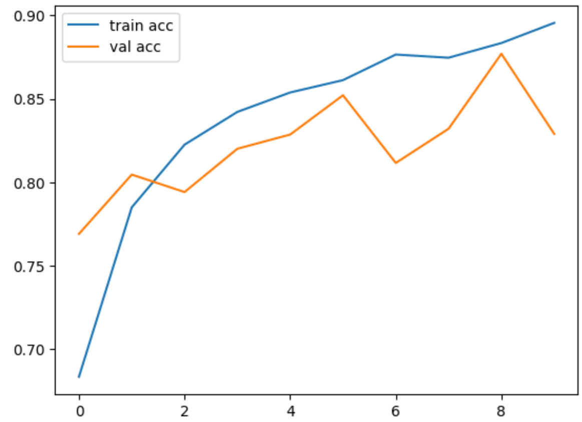


Figure 4: InceptionV3 Model

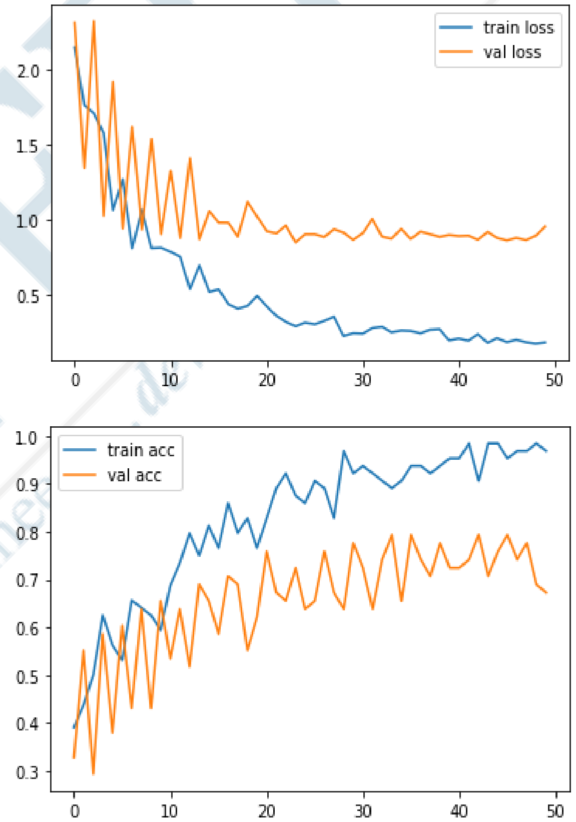


Figure 5: ResNet50 Model

REFERENCES

[1] Balwant J Gorad, Dr. S. kotrappa, "Comparativ Study and Review for Development of Disease Prediction System of Indian Crops", IOSR Journal of Computer Engineering (IOSR-JCE), Vol. 21, pages 68-73, (2019).

[2] R. Neela, and P. Nithya, "Fertilizers Recommendation System For Disease Prediction In Tree Leave", International Journal of Scientific and Technology Research, Vol. 8, (2019).

[3] Samhitha Suda, Dr. C N Sujatha, "Leaf Disease Detection And Classification", National Conference on Advances in Electronics Signal Processing and Communications (2020)

[4] Pranesh Kulkarni et al., “Plant Disease Detection Using Image Processing and Machine Learning”, (2021).

[5] Arvind Kumar Shukla, Rajdeep Singh, C. K. Dixit “A study based on plant disease prediction system using machine learning”, Turkish online journal of qualitative inquiry(TOJQI), Vol. 12, (2021).

[6] Houda Orchi, Mohamed Sadik, Mohammed Khaldoun “On using artificial intelligence and the internet of things for crop disease detection: A Contemporary survey”, Agriculture, (2021).

[7] Pallepati Vasavi, Arumugam Punitha, Venkat Narayana Rao, “Crop leaf disease detection and classification using machine learning and deep learning algorithms by visual symptoms: a review”, International journal of Electrical and computer engineering (IJECE) vol-12, no. 2 (2022).

[8] Mohammad Hussein Najim, Salwa Khalid Abdulateef et al., “Early Detection of tomato leaf disease based on Deep Learning techniques”, IAES International Jouranl of Artificial Intelligence, Vol. 13, pages 509-515, (2024).

[9] Anita S. Kini, K. V. Prema and Smitha N. Pai, “Early stage black pepper leaf disease prediction based on transfer learning using ConvNets”, Scientific Repots (2024).

[10] Atul B. Kathole, Kapil Netaji et al., “IoT-Based Smart Agriculture for Onion Plant Disease Management: A Comprehensive Approach”, International Journal of Intelligent Systems and Applications in Engineering, 12(13s), pages 472-476, (2024).

[11] Munaf Mudheher Khalid, and Oguz Karan, “Deep Learning for Plant Disease Detection”, International Journal of Mathematics, Statistics, and Computer Science, Vol. 2, (2024).

[12] Rehyan Dzaki Sheva, Halimah Salsabila and Kusuma Ratna Pratiwi, “Detection and Prediction of Rice Plant Diseases using Convolutional Neural Network (CNN) method”, Journal of Student Research Exploration, Vol. 2, pages 22-33, (2024).