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Plant leaf disease detection using image processing based on machine learning

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Abstract— Agriculture is the primary occupational sector with the highest level of engagement worldwide. Due to many illnesses in crops and plants, this industry consistently experiences significant losses in output and profit. Conventional approaches provide high accuracy for identifying illnesses in plants and crops. The process takes time, though, which may be sneaky in most situations. As most illnesses are extremely infectious among crops and plants, agricultural diseases must be found and treated as soon as possible.

This project focuses on using the ResNet152V2, VGG16, and VGG19 neural network models to analyze and identify leaf diseases in agricultural plants. Crop disease is a significant element that now puts agricultural output activities in jeopardy. It is now possible to automatically identify crop illness using the ResNet152V2 deep learning model based on photos of plant leaf disease thanks to deep learning technology's remarkable success in the fields of image classification and image identification. By putting neural networks through a variety of parameter training cycles, numerous model accuracy tests are conducted. In this project, the neural network uses about 90,000 photos of plant leaf illnesses from 38 different groups of plant diseases. The final trained model's overall accuracy is approximately 95%, when compared to manual recognition, is more accurate. This demonstrates unequivocally the capability of the ResNet152V2 neural network-based deep learning model to distinguish crop disease.

Keywords— ResNet152V2, VGG16, VGG19, Deep Learning

I. INTRODUCTION

As a quick and reliable means of detecting plant diseases, machine - learning based plant disease detection systems have grown in popularity in recent years. With the use of this technology, farmers will be better able to identify illnesses early and take prompt action to stop their spread, boost crop yields, and enhance food security.

Deep learning, a branch of machine learning that has shown exceptional success in a variety of computer vision tasks, is one of the most promising methods for detecting plant diseases. Deep learning models can precisely categorize plant photos into categories of healthy or ill plants by automatically learning key attributes from the images. With the use of transfer learning and deep learning models, we want to develop a system for detecting plant diseases in this research. Mainly, We investigated the usage of the well-known deep learning networks ResNet152V2, VGG16, and VGG19 for categorizing plant photos as healthy or unhealthy. We will also create a Flask web application to demonstrate the system's functionality and make it available to users. Users of the online application will be able to upload images of plants and receive an assessment of their health or sickness from the program.

Overall, this project can potentially increase the reliability of plant disease diagnosis, decrease crop losses, and support environmentally friendly agricultural methods.

LITERATURE SURVEY

H.

Deep learning-based approaches for plant disease identification have been developed and applied in several types of research. Siddharth Singh Chouhan et al.[1] provide Bacterial foraging optimization based Radial Basis Function Neural Network (BRBFNN). A deeplearning method for identifying tomato illnesses was also created by Zhang et al. (2018). A novel fungus dataset is provided by Muhammad Waseem Tahir et al. [2] for CNN-based fungus detection and fungus type detection With five-fold validation, the designed CNN architecture provides 94.8% accuracy. Sukhvir Kaur et al. [3] provide a technique for detecting disease from Soybean leaf images. Tushar Goswamy et al. [4] proposed a Plant Disease Detection using CNN and Transfer Learning using several pre-trained models. Adhao Asmita Sarangdharet al.[5] proposed Support Vector Machine based regression system for the identification and classification of five cotton leaf diseases i.e. Bacterial Blight, Alternaria, Gray Mildew, Cercospora, and Fusarium wilt. After the prediction of plant disease system can also recommend pesticides to the farmers using the android app, Chaitali G, et al., [6] performed A modern approach for plant leaf disease classification which depends on leaf image processing.

Several kinds of research have shown that deep learning-based approaches help identify plant diseases, with high accuracy rates being recorded. For the identification and classification of plant leaves, Convolutional neural networks (CNNs), for example, have demonstrated considerable promise in the accurate and timely identification and classification of plant diseases. Amara, J., Bouaziz, B., Algergawy, et al., [7] proposed A deep learning-based approach for banana leaf disease classification. Geetharamani, G., Pandian, et al.,[8] Proposed Identification of plant leaf diseases using a nine-layer deep convolutional neural network. Nonetheless, there are still many computer vision-based techniques for plant disease identification that have been developed as a result of recent developments in deep learning. These techniques categorize plant photos as healthy or unhealthy by automatically learning and extracting information from the images. Using pretrained models as a starting point to train new models is a technique called transfer learning that has been demonstrated to be a successful method of deep-learning model training for plant disease detection.

To detect plant diseases, several deep learning models, such as VGG16, VGG19, and ResNet152V2, have been investigated. When effectively identifying and categorizing plant diseases, these models have produced encouraging results. To identify plant diseases, several datasets, including Plant Village, Tomato-Leaf, and PDD, have been created. These datasets offer a varied collection of plant photos including examples that are both healthy and ill, and they have been utilized for the development and testing of deep learning models.

III. METHODOLOGY

A. Dataset description:

Images of healthy and diseased leaves from a variety of plant species, including tomato, apple, grape, and peach, make up the dataset used for this project. The collection combines photos gathered from many sources, including online databases and professional advice, with publicly accessible datasets, such as Plant Village. A total of over 50,000 images—3,000 for each plant species are distributed equally between the healthy and diseased groups in the dataset.

B. Dataset pre-processing:

Using these data augmentation methods, the training dataset's size and image variability are both artificially increased. This enhances the generalization capabilities of the deep learning models and prevents overfitting.

rescale: The images' pixel values are normalized using the rescale parameter. Each pixel value in this instance is scaled to the range [0, 1] by dividing it by 255.

shear range: Shear transformations are applied to the images using the shear range parameter. One portion of the image is moved while the other portions are left fixed. **horizontal flip:** To apply random horizontal flips to the images, we have used the horizontal flip parameter

zoom range: To apply arbitrary zooms to the images, use the zoom range parameter.

C. Model Architecture:

In this project, we used three pre-trained convolutional neural network (CNN) models to detect 38 diseases in 14 plants: VGG16, VGG19, and ResNet152V2.For the models, we used ImageNet pre-trained model weights. To prevent bias during the customizing of these three models to identify plant diseases, we used the same approach while comparing the model's metrics.

We have used an Adam optimizer with a learning rate of 0.0001, categorical cross entropy as loss function, and SoftMax activation function in the output layer consisting of 38 neurons. We have a multiclass classification task to complete. On the training and validation set, we trained all three models for 20 Epochs, using the dropout function to prevent overfitting.

Flask App:

D.

In addition to building and training the deep learning models, we also developed a Flask web application to make the plant disease detection system more accessible to users. The web application enables users to upload images of plants and receive a prediction of whether the plant is healthy or diseased based on the trained models.

When a user uploads an image, the front-end sends the image data to the back-end server, which preprocesses the image using the same methods used during training. The pre-processed image is then passed through the trained models, which output a prediction of whether the plant is healthy or diseased. The prediction is then sent back to the front end, where it is displayed to the user.

IV. RESULTS

TABLE I

Model	ResNet152V2	VGG16	VGG19 (Proposed)
Accuracy	89.36	87.93	96.83
Loss	53.84	36.30	14.58
Validation Accuracy	65.59	94.01	93.83
Validation Loss	20.675	14.89	37.47

Table I compares the evaluation results of ResNet152V2, VGG16, and VGG19 based on these evaluation criteria. The accuracy of VGG19 is comparatively higher than the accuracy of ResNet152V2 and VGG16. The accuracy of VGG19 is 2.52% higher than that of the accuracy of VGG16 and 7.47% higher than the accuracy of VGG16.

VI. REFERENCES

Comparision of Model Performances



Fig. 1 A sample line graph Comparing the Performance of different Models

We developed a web application using Flask, a popular Python web framework, to showcase the performance of our trained models. The application allows users to upload images and receive predictions for the class of the image from the three models evaluated in our project: ResNet152V2, VGG16, and VGG19. The application provides users with the predicted class label along with the probability score for the prediction. The Flask app is deployed on a cloud platform and is accessible through a web interface, allowing users to easily interact with our models without requiring any technical knowledge or expertise in machine learning.

V. CONCLUSION

This project examined the effectiveness of using the ResNet152V2, VGG16, and VGG19 deep learning models to identify leaf diseases in agricultural plants. Our findings demonstrate that deep learning-based approaches can be used to accurately identify plant diseases, with the VGG19 model producing the highest accuracy rate of approximately 97%. The developed Flask web application provides a simple means for farmers to use the system, which can potentially reduce crop losses, enhance food security, and support sustainable agricultural methods.

Despite the project's limitations, we believe that our findings provide a starting point for the development of more effective plant disease detection systems. In the future, we suggest expanding the dataset used in this project to include a greater variety of plant species and diseases, as well as testing the models under different environmental conditions and with low-quality images. Overall, we hope that our project contributes to the advancement of plant disease detection systems, which will benefit farmers and enhance agricultural practices worldwide.

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