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PLANT DISEASE DETECTION USING DEEP LEARNING

Abstract-- **Global food security is seriously threatened by plant diseases, which can result in large crop losses. The detection of plant diseases may be done more quickly and accurately with the use of cutting-edge technology like neural networks, enabling effective management plans. By examining photos of leaves, stems, and other plant components, neural networks, in particular convolutional neural networks (CNNs), have been effectively used in the identification of plant diseases. This study provides a thorough analysis of current developments in neural network-based plant disease identification. The study emphasises the value of identifying plant diseases in agriculture and the potential of neural networks to increase disease detection precision. The various designs and training methods utilised for neural network-based plant disease identification are also covered in the paper. The issues with data accessibility, environmental variability, and the generalisation of neural network models still exist. Overall, this study illustrates the value of using neural networks to the detection of plant diseases and the possibility for further development in this area.**

I. Introduction

FINDINGplant diseases early on is crucial for crop management and for safeguarding the safety of the world's food supply. Early disease diagnosis can reduce crop losses and prevent the spread of the illness. Plant disease detection has been increasingly accurate and successful in recent years because to the adoption of cutting-edge technology and analytical techniques. The significance of plant disease detection will be covered in this article, as well as how it may be enhanced with the use of cutting-edge equipment and analytical techniques.

Global food security is seriously threatened by plant diseases, which have an effect on the whole agricultural sector. Diseases can result in severe crop losses, worse crop quality, and higher production costs. Plant diseases have a potential to increase food costs and have an annual economic impact estimated to be in the billions of dollars.

For the purpose of controlling crop losses and halting the spread of illness, early diagnosis of plant diseases is essential. Farmers can manage the illness by eliminating contaminated plants or using the right medicines with the aid of rapid diagnosis. Early identification can lessen the overall impact on the agricultural sector by assisting in the prevention of the disease's spread to nearby crops.

The identification of plant diseases can be enhanced by the application of cutting-edge technology and analytical techniques. For instance, remote sensing tools like satellites and drones may be used to spot changes in vegetation patterns that could be signs of illness. Additionally, DNA-based diagnostic tools can be used to quickly detect the presence of particular pathogens in plants, enabling the development of targeted management techniques.

Additionally, by analyzing sizable datasets of data on plant health, machine learning algorithms can be used to spot patterns that might point to the presence of disease. With the use of these technologies, predictive models may be created that will enable farmers to foresee disease outbreaks and take preventive measures.

Finding plant diseases early on is crucial for crop management and for safeguarding the safety of the world's food supply. By utilizing cutting-edge technology and analytical techniques, plant diseases may be detected more quickly and accurately, enabling farmers to treat the illness and lessen its effects on crop output. We can support the agricultural sector's protection and guarantee a dependable and sustainable food supply for future generations by investing in the early diagnosis of plant diseases.

Deep learning algorithms known as convolutional neural networks (CNNs) may be used to analyze photos and find patterns. CNNs may be trained to recognize the visual signs of plant illnesses in pictures of leaves, stems, and other plant components in order to detect plant diseases. Even in large-scale agricultural contexts, this enables quick and precise disease diagnosis.

There are various advantages of using CNNs to identify plant diseases. First, CNNs are capable of precisely identifying diseases in their earliest stages, enabling farmers to manage them early on and stop their spread. Second, illnesses that are challenging to detect with the naked eye can be identified by CNNs, increasing the overall accuracy of disease detection. Last but not least, CNNs may be taught to recognise certain diseases, enabling focused management approaches that can lessen the overall burden of disease outbreaks.

The ability to quickly and accurately detect plant diseases is essential for preserving the security of the world's food supply. CNNs are a cutting-edge technology that can help in this endeavour. We can safeguard the agricultural sector and guarantee that we have a dependable and sustainable food supply for future generations by investing in plant disease detection utilising CNNs.

II. Literature Review

In this paper, the authors presented INAR-SSD, a new network architecture constructed using VGGNet and Inception. They applied the architecture for the detection of apple leaf disease and attained 78.8% mAP [1].

In this paper, the authors used Triplet loss and SVM as an improved method for the recognition of plant leaf diseases. They derived the source and target domains dataset from the PlantVillage dataset. The final 50 layers of the 315 layered Inception V3.0 model were fine-tuned. Using Triplet loss to generate an embedding space and SVM classifier for FSL, their results surpassed those of the fine-tuned model [2].

The study introduces an improved Faster R-CNN architecture, which involves modifications to a CNN model's parameters, to automatically detect leaf spot disease (Cercospora beticola Sacc.) in sugar beet. The proposed method relies on expert systems based on imaging to evaluate disease severity, and it was trained and tested using 155 images. Results indicate an overall accuracy rate of 95.48% for disease classification [3].

The authors of this study developed a technique to classify various plant diseases by utilizing the deep learning model called EfficientNet. To train the model, they employed the Plant Village dataset containing 55,448 images and an augmented version of the dataset with 61,486 images. The performance of the proposed EfficientNet model was compared to other state-of-the-art CNN models, such as ResNet, VGG, AlexNet, and Inception. EfficientNet is different from other CNN models in that it uses an activation function known as Swish, as opposed to the commonly used Rectifier Linear Unit (ReLU) activation function. In transfer learning, all layers were set to trainable. According to the results, EfficientNet B5 and B6 models had the highest performance among all the models tested [4].

In this paper, a lightweight CNN model was created by compressing VGG16 using a process that involved obtaining the weights of filters from hidden convolution layers, sorting and selecting the top relevant weights, and creating a list with 1s for substantial weights and 0s for negligible weights. The number of substantial weights was used to create a new CNN model with those number of nodes/filters, and weights from the previous CNN model were copied where there was a 1 in the list for that hidden layer. The model achieved a maximum accuracy of 98.4% after 5000 epochs [5].

The objective of the study was to develop two deep learning models to identify the type of infection in tomato leaves using the Plant Village Dataset. The first architecture used residual learning to recognize significant features for classification, while the second architecture added an attention mechanism to further improve performance. The models achieved an overall accuracy of 98% on the validation sets using a 5-fold cross-validation process [6].

This study aimed to develop accurate models for identifying plant diseases. 38 different classes of plant leaf images were used to evaluate the performance of various deep convolutional neural network architectures, including VGG 16, Inception V4, ResNet, and DenseNets. The results showed that DenseNets consistently outperformed the other architectures in accuracy, requiring fewer parameters and reasonable computing time to achieve state-of-the-art performances. DenseNets achieved a testing accuracy score of 99.75%, indicating their potential for accurate and efficient plant disease identification [7].

In this study, a new dataset containing 79,265 images were used. Two methods were employed to increase the number of images in the dataset: conventional augmentation techniques and modern style generative adversarial networks. The novel architecture, PlantDiseaseNet, has been used here. It's a two stage network, with the first layer being the combination of AlexNet feature extractor and YOLO classifier, and the second layer being a classification 34-layer network built of 3×3 residual block filters with a global average pooling layer on the top along with a 42-way fully-connected layer with a Softmax layer at the end. The accuracy achieved was 93.67% [8].

In this paper, a lightweight two-stage CNN architecture is suggested as a more suitable option for mobile devices when compared to larger scale architectures. The proposed architecture is compared with other memory-efficient CNN architectures such as MobileNet, NasNet Mobile and SqueezeNet, and the experimental results indicate that it can attain an accuracy of 93.3% with a much smaller model size. In fact, the model size is 99% smaller than that of VGG16 [9].

In this research paper, a novel method for detecting anthracnose lesions in apples using deep learning is proposed. Traditional image augmentation techniques are utilized alongside the Cycle-Consistent Adversarial Network (CycleGAN) deep learning model for data augmentation. Additionally, the feature layers of the YOLO-V3 model with lower resolution are optimized using a densely connected neural network (DenseNet). The accuracy achieved by this YOLOV3-dense model is 95.57% [10].

Mini-batch gradient descent algorithm can be trained as it has low computational complexity and increases the efficiency of model. Their deep CNN model detects 97.87 % of total images correctly with 3000 epochs. Model performs good with dataset containing augmented images than the one with non-augmented images [11].

In this study, plant illnesses are identified from photographs of plant leaves and properly classified into two groups depending on the presence or absence of disease using Deep Convolutional Neural Network (CNN). A tiny neural network with an accuracy of 96.6% is trained using a modest dataset of 1400 photos [12].

Plant disease detection is carried out with image processing. Image collection, image pre-processing, picture segmentation, feature extraction, and classification are procedures involved in the disease detection process. Image processing is often used to reliably identify and categorize plant diseases, that is essential for ensuring the successful growth of crops [13].

A platform committed to crop health and crop diseases called PlantVillage is based on popular sites for computer programming. It created a library of free, open access information on 150 crops and 1,800 diseases written by experts in plant pathology and has seen a 250% increase in traffic year over year. For food growers, machine-assisted disease diagnosis has the potential to be an extremely useful tool. The two most crucial points in this text are that a computational diagnostic tool should be able to support the human diagnostician and that an online computational system that could help with disease diagnosis would be both extremely helpful and inherently scalable [14].

This study provides CNN based web application that has potential to detect carrot disease if an image is given as input. Their model classifies whether the carrot is healthy or ill with an accuracy of 99.8 % [15].

This study proposes a model that were built using Convolutional Autoencoder Network (CAE) and Convolutional Neural Network (CNN) with very less number of parameters when compared to other plant disease detection models. For training, PlantVillage dataset was used with less than 5000 images. This system predicts correctly with 99.35% training accuracy and 98.38% testing accuracy [16].

The detection of plant diseases may be done effectively using deep learning. This research suggests a unique CNN model with improved performance accuracy that is based on the inception and residual connection. Three distinct plant datasets have been used for testing, with accuracy rates of 99.39%, 99.66%, and 76.59% respectively. Future work will examine how the proposed model performs in various agricultural fields while utilising clustering-based unsupervised techniques [17].

This study suggests a unique deep convolutional neural network model to recognise apple leaf diseases with high accuracy. A deep convolutional neural network with a new structure based on the AlexNet model was created using a dataset of 13,689 photos of sick leaves. The suggested model outperformed previous models with a recognition accuracy of 97.62%. Other deep neural network models, like Faster RCNN, YOLO, and SSD, will be used in upcoming research to detect more diseases in real time [18].

The neural network is learning to focus on visual features correlated with disease and the shape of the leaf to help it distinguish between species. Results show low accuracy when processed initially with ImageNet or PlantVillage. Faster R-CNN with InceptionResnetV2 performs best with an mAP of 38.9. MobileNet performance is decreased when pre-trained on COCO+PlantVillage compared to the model where pre-training was done only on COCO. This paper proposes a new dataset for plant disease detection called PlantDoc, which uses state-of-the-art object detection models to detect diseased/healthy leaves in images [19].

In order to classify tomato plant illnesses, this research developed a DL strategy combining CNN pre-trained models with fine-tuning. With various performance metrics, it compared the effectiveness of AlexNet, GoogleNet, Inception V3, ResNet 18, and ResNet 50. The objective was to identify the model that was most suited to the job. Nine illnesses in tomato leaves from the healthy class could be classified using all models, with GoogleNet achieving a 99.72% accuracy rate. Despite having the most layers, Inception V3 had the worst performance. The proposed approach is anticipated to significantly advance the field of agriculture [20]

III. OBJECTIVE

The objective of the research on plant disease detection using CNN is to develop a reliable and automated system for early detection and accurate diagnosis of plant diseases. The proposed method involves using convolutional neural networks (CNN) to learn the discriminative features from plant images and classify them into healthy or diseased categories. The objective is to achieve high accuracy rates for disease detection, outperforming other state-of-the-art methods. The ultimate goal of the research is to help farmers increase crop yields and improve food security by enabling them to take preventive measures and minimize crop losses. Additionally, the research aims to demonstrate the potential of machine learning and computer vision techniques in revolutionizing the way plant diseases are detected and controlled.

IV. METHODOLOGY

1. Data Collection: The PlantVillage dataset has been used. It consists of 54303 healthy and unhealthy leaf images divided into 38 categories by species and disease, such as Black Rot (Apple), Powdery Mildew (Cherry), Northern Leaf Blight (Corn), Leaf Blight (Grape), Late Blight (Potato), Leaf Mold (Tomato), etc.

Figure 1: Sample images

2. Data Preprocessing: To insert the image data into the CNN model, , some image pre-processing are mandator such as scaling each image and resizing image. Scaling and resizing has been done as part of preprocessing.

3. Data Augmentation: Augmentation has been used to increase the dataset size. For this, imgaug library of python has been used. Horizontal flip, Vertical flip, Rotation, Shear, methods have been used. An image augmentation algorithm needs to be implemented to improve model training and prediction.

4. Model Architecture: The number and size of the layers depend on the complexity of the problem and the available computational resources. A 6-layered CNN model architecture has been used. This typically involves stacking multiple convolutional, pooling, and fully connected layers. The activation function used for the hidden layers is ReLu and final layer SoftMax.

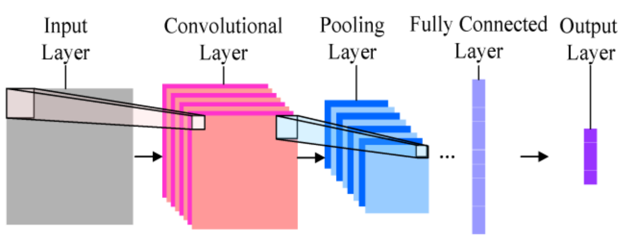


Figure 2: Architecture of a Single Layer CNN

Figure 2 represents a simple CNN with single convolutional layer. First comes input layer that takes the scaled pixel array of each image, then there is a convolutional layer along with pooling layer. All the filtration happens in these layers. Fully connected layer connects all previous layers and forms a final array, then the final array is used for classification. Different class labels have different array distribution. Based on that, we are able to classify target classes with a CNN model.

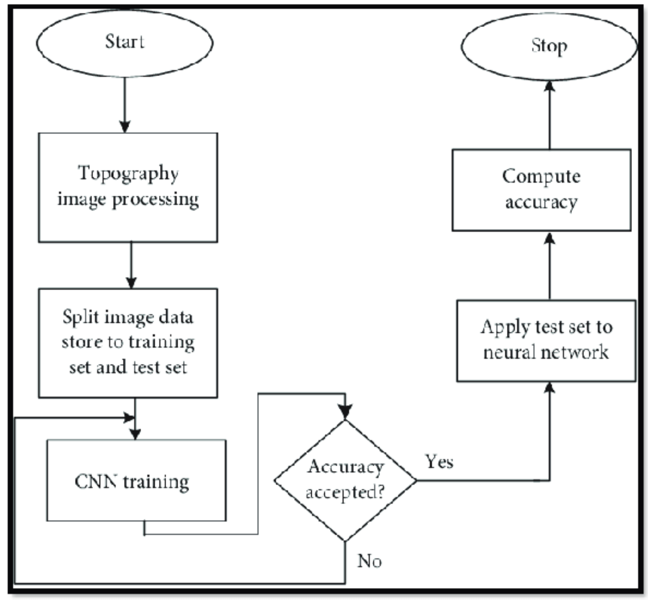
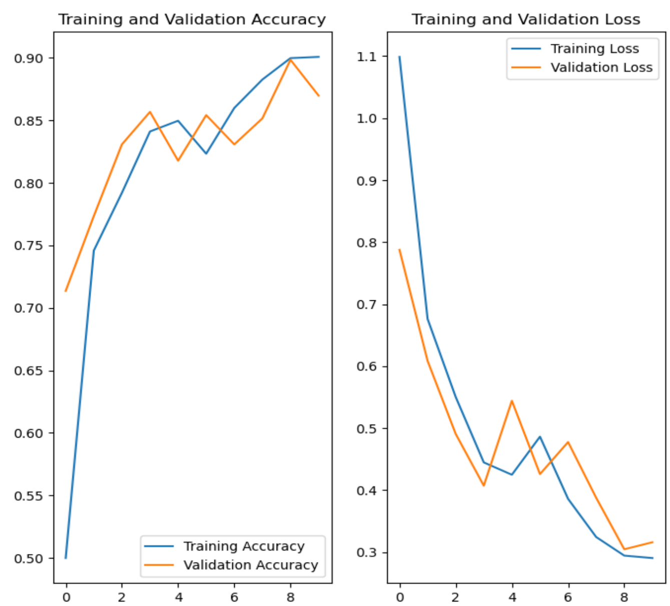


Figure 3: Flowchart

V. Result

After 10 epochs, we get an accuracy of 90.08 % with a batch size of 128. The accuracy is quite good considering the size of the dataset.



VI. Conclusion

The created CNN model has demonstrated good effectiveness in detecting plant diseases. It delivers good accuracy rates when categorising plant pictures as healthy or unhealthy. The use of convolutional layers allows the model to learn and extract discriminative features from plant photos, capturing the distinct properties associated with various illnesses. This research helps to increase food security and agricultural production by using the power of machine learning and computer vision techniques. This approach's dependable and automated method helps farmers with early identification and precise diagnosis of plant diseases. This, in turn, enables farmers to quickly adopt preventive measures, reducing the likelihood of substantial crop losses.

In conclusion, the research demonstrates the value of using CNNs for plant disease detection. The results indicate the potential of neural networks to revolutionize the detection and control of plant diseases, thereby enhancing food security and supporting sustainable agriculture practices. Further developments in data collection, model architecture, and training techniques can lead to even more accurate and robust plant disease identification systems in the future. It is crucial to emphasise, however, that obstacles remain in the field of plant disease detection utilising neural networks. Data accessibility and environmental variability provide obstacles in acquiring representative and varied datasets. Furthermore, the generalisation of neural network models to hitherto unknown situations and plant species requires additional investigation.

Finally, the study indicates the utility of employing CNNs for plant disease detection. The findings suggest that neural networks have the potential to revolutionise the identification and control of plant diseases, ultimately improving food security and promoting sustainable agriculture practises. Future advances in data gathering, model design, and training methodologies may result in even more accurate and robust plant disease diagnosis systems.

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