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A Deep Learning Method for Plant Disease Diagnosis and Detection in Smart Agriculture

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ABSTRACT

The first step in precise and efficient disease prevention in an environment that is notoriously challenging to work in is the identification of plant diseases. The rapid expansion of "smart farming" has made it possible to make better decisions, analyses, and plans. An algorithm based on deep learning is proposed by the study's author to diagnose and identify plant diseases. This approach might improve training's efficacy, accuracy, and generality. Both the ResNet101 and DenseNet12 pre-train models are used in this study's transfer learning implementation. This model was tested using the Plant Village data set, which has been divided into training and testing phases. The next step is data preparation, followed by up sampling, CLAHE image enhancement, and then the various hyperparameters. In addition, the model is checked for bacterial plaque, black rot, and other issues. The method's accuracy is 98.37 percent, which is higher than that of the previous approach. As a result, crop yields are less affected by the disease, which is good for agriculture's long-term expansion. As a result, the research's deep learning algorithm is crucial to the fields of intelligent agriculture, environmental conservation, and agricultural productivity.

Keywords : Plant Disease Classification, CNN, Deep Learning, Transfer Learning, Dense-Net, Res-Net.

I. INTRODUCTION

The Indian economy is primarily supported by the agricultural sector. Agricultural image processing is one of the most significant applications of image processing and one of the fastest-growing research fields. Image processing has proven to be a useful tool for conducting analyses in a variety of industries, including agriculture. Image processing in agriculture starts with the taking of pictures, which can be accomplished with cameras, aircraft, or satellites[1]. Computers are used to carry out the processing and analysis of these images using image processing techniques. It has become much easier to find solutions to a variety of problems that arise in the agricultural industry as a result of recent technological advancements in image capture and data processing. Image processing can be used in agricultural applications, among other things, to achieve the following objectives: The fruit, stem, and infected portions of the leaf must be removed. Calculate the area that has been impacted by the disease after identifying the disease based on the color, shape, and size of the affected area[2].

It is possible for bacteria to spread thru the contaminated seed, transmission material, and crop residues. It is also possible for bacteria to spread through water splashes as well as wind-driven rain, contaminated equipment, as well as the hands of employees. Bacteria that live in plants are capable of causing damage to the plant's stems, leaves, or roots, or they are capable of moving within the plant without causing any outwardly apparent symptoms. Plants that are infected with bacterial diseases may exhibit a variety of symptoms, including wilts, cankers, leaf spots, overgrowths, scabs, and other abnormalities. Plants are susceptible to a wide variety of bacterial diseases, the most common of which are citrus canker and potato scab[3].

The large bulk of plant-infecting pathogens are fungi, which are also the causative agents of a wide variety of debilitating plant diseases. The vast majority of illnesses that can be transmitted from plant to plant are caused by fungi. The seed, soil, crop, as well as weeds that have been infected with a fungal disease, are the most common carriers of the infection[4]. At an early stage, it appears as water-soaked, gray-green spots on the lower as well as older leaves of the plant. These patches are found on older leaves. These spots will eventually become deeper, and shortly after that, white fungal growth will begin to spread across the undercarriage. Infections caused by fungi can take many different forms and can have a wide range of effects on crops. There are a number of diseases that have the potential to cause this, including anthracnose, botrytis rots, downy mildews, fusarium rots, and powdery mildews[5].

Figure 1. Leaf Diseases

The classification and recognition of crop diseases are of primary technical and commercial relevance in the Agricultural Industry. Agriculture image processing starts with the digitized color image of a sick leaf. Observation of health and detection of illnesses in plants is crucial for property agriculture. Plant diseases have impacted civilization and worldwide[6]. The classification tactics are expansions of the detection strategies, however, rather than aiming to observe just one specific sickness amidst totally varied situations and symptoms, these ones attempt to determine and classify whichever pathology causes consequences on the plant. Plant pathologists will study the plant photos in diagnosing of crop diseases. Computer Systems area unit designed for agricultural applications, like detection of leaf diseases, fruits illnesses, etc[7] [8].

In conclusion, approaches from the field of machine learning are utilized for the training and testing of image sets. In the field of machine learning, disease detection and categorization are primarily accomplished through the use of classification strategies. There are a wide variety of approaches that can be taken to classify things. Classification is used in the interpretation of the extracted diseased region in an image, which helps in the identification of the type of disease infection in leaves. This is accomplished by using the image[9].

II. LITERATURE REVIEW

Abu Sarwar Zamani et al. Images of contagious leaf diseases are being studied for this study. In precision agriculture, automated leaf disease identification is achieved through the use of machine learning in tandem with state-of-the-art image processing, picture segmentation, and feature extraction. Using an automated disease detection system, a farmer can get a quick and accurate diagnosis of a plant's illness. Automation of the plant leaf disease sensing system is necessary for faster identifier of agricultural diseases. In this study, we present a method for automatically diagnosing leaf disease using machine learning and image processing. This architecture takes as input a picture of a leaf. First, during the preprocessing phase, noise is removed from the leaf images. The mean filter is a method for reducing background noise. Histogram equalisation is a tool for enhancing an image's quality. In photography, segmentation is the practise of cutting a whole picture up into smaller pieces. This facilitates the process of determining the scope of a photograph. To achieve this separation, we employ the K-Means algorithm. Features are extracted using principal component analysis. Afterwards, image classification methods such as RBF-SVM, SVM, random forest, and ID3 are utilised[10].

K. Lakshmi Narayanan et al. Indian farmers lose a lot of money if they don't use pest signals to catch diseases early on their banana crops. The national economy will feel the effects of this problem because it will affect banana production nationwide. Banana disease has been detected using hybrid convolutional neural networks (CNNs), and the classification has been suggested to guide growers through enabling fertilisers that must be used to avoid the disease in its early stages. The proposed technique demonstrates 99.1% accuracy when compared to the related deep learning techniques[11].

Iftikhar Ahmad et al. Plants that produce vegetables and fruits are essential to human survival, as they provide food for an estimated 7.5 billion people around the world. More and more chemicals, like fungicides and bactericides, are being used to combat plant diseases, but this has unintended consequences for the environment. Damage from plant diseases reduces yields and lowers overall crop quality. To help solve the issue of early disease identification and diagnosis, a fast and consistent reliable method is needed. In this study, we investigate whether it is possible to classify and identify tomato leaf diseases using convolutional neural network (CNN) techniques. We investigate four CNN architectures—VGG-16, VGG-19, ResNet, as well as Inception V3—and employ feature extraction as well as parameter tuning to detect and categorise diseases affecting tomato leaves. The models are put to the test using both a controlled laboratory dataset and self-collected field data. We find that across all metrics, laboratory-based datasets outperform field-based datasets by 10% to 15%. Inception V3 was the most effective algorithm for both datasets[12].

Marwan Adnan Jasim et al. [2020] Agricultural goods are the top priority for every nation. When plants are afflicted by diseases, it reduces agricultural output and drains national resources. In this study, we apply deep learning methods to the problem of disease detection and classification in plant leaves. The pictures used in this venture came from the (Plant Village dataset). Among the most widely grown crops worldwide are tomatoes, peppers, and potatoes; in Iraq, these three crops dominate the agricultural landscape. The 20636 images in this set depict both healthy plants and those that have been infected. We were able to classify 15 different types of plant diseases using the convolutional neural network (CNN), including 12 types of plant diseases (such as bacteria, fungi, and so on) and three types of healthy leaves. We were able to train with a 98.29% accuracy and test with a 98.029 percent accuracy across all datasets[13].

Surampalli Ashok et al. The early diagnosis of plant leaf blight is crucial in a developing agricultural economy such as India's. The security of the agri-based economy as well as the prevention of losses for the large population depend on the early detection of leaf diseases in plants and the adoption of predictive mechanisms. Image classification techniques, clustering, as well as open-source algorithms can be used to process images of Tomato Plant Leaf disease, leading to a more reliable, secure, and accurate system for trying to identify leaf disease in Tomato Plants[3].

III.Proposed Methodology

A. Image Actuation

Taking a picture is the first stage of the system. The Kaggle-collected PlantVillage dataset was used in the study. We typically take pictures of both healthy and diseased subjects when using a digital camera, and the process of loading an image is a representation of this. The effectiveness is directly related to the quality of the images used.

B. Image preprocessing

Next, we put some preprocessing methods for images to use. Information content of original images is not improved by processing at the lowest level of abstraction (image pre-processing). Generally speaking, image pre-processing is done to improve the image and get rid of any distortions. Noise employed a number of methods for bettering the contrast and information content of the images it was processing.

C. Data Augmentation

In addition, we employed data augmentation methods to further improve the extracted photos. By using data augmentation, professionals can significantly expand the data pool used to train models without collecting any new information. Common data augmentation techniques used to train large neural networks include cropping, padding, and horizontal flipping. The term "data augmentation" is used to describe a variety of methods for boosting the quality and quantity of training datasets in order to develop more accurate deep learning models.

IV.Proposed Model

In particular, Deep Learning models have made tremendous strides in improving at discriminative tasks. Progress in deep network architecture, fast computers, and easy access to large amounts of data have all played a role. Convolutional neural networks have allowed for the successful application of deep neural networks to Computer Vision tasks like image classification, object identification, as well as picture segmentation (CNNs). Parameterized sparsely connected kernels are utilised in these neural networks to preserve spatial characteristics of images. The spatial resolution of an image is progressively lowered while the detail of its feature maps is raised using convolutional layers. These convolutional transformations could result in much lower-dimensional and practical picture representations than would be possible by hand. The popularity of CNNs has increased interest in using Deep Learning to solve issues in Computer Vision[14].

1.1 Transfer Learning

Networks trained on millions of images can be used to train networks for tasks with fewer data points, making transfer learning a potent representational learning strategy (a few hundred or thousand images). In the field of deep learning, there are two common methods for applying transfer learning from pretrained networks. In the first method, only the weights of some of the newly added layers are optimised during training, while in the second method, all of the weights are adjusted to better suit the new task[15].

A. ResNet

The winning network is 152 layers deep, proving that more complex networks produce superior representations in the visual realm. However, there are two main problems that arise when training networks of increasing depth: vanishing gradients and performance degradation. To prevent further data loss as the network grew in depth, the authors implemented skip links as a solution. The ResNet-101 network is a deep convolutional neural network with 101 layers[16]. The network can be imported in a pretrained state, which has been trained on more than a million images available in the ImageNet database.

The pretrained network can sort pictures into one thousand distinct categories, such as animals, plants, and various types of office equipment. Thus, the network has picked up complex feature representations for a wide variety of images[17].

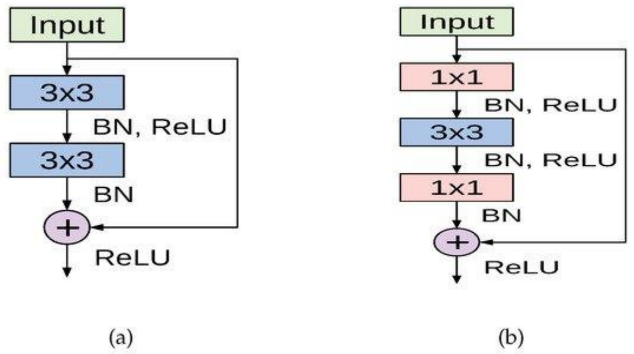

Figure 2. The ResNet fundamental residual module[15]

In Figure 2 we see two different implementations of the residual module, which serves as the basis for developing deep residual networks. Figure 1a shows the left route of the residual module, which is constructed from two convolutional layers using 33 kernels while maintaining the spatial dimensions. In addition, ReLU activation and batch normalisation are employed. The input is simply added to the left path's output via a skip connection, which is the right path. It is used in the ResNet18 model. Figure 1b shows a second type of residual module, the bottleneck residual module, in which the input signal also splits into two paths. On the other hand, the left path employs batch normalisation as well as ReLU activation in addition to a series of convolutions with 11 and 33-size kernels. The input of the module is connected to an addition operation via the skip connection, and the right path receives the output of the left route.

B. DenseNet

DenseNet is a novel approach to increasing the size of deep neural networks without running into problems such as growing as well as vanishing gradients. Each layer has direct links to the ones below and above it, facilitating the free flow of data and gradients. At this point, everything should be fine. The goal is to maximise symbolic power through feature reuse instead of relying on massive, deep, or wide CNN architectures. In comparison to conventional CNNs, DenseNets can function with fewer or the same number of nodes. For the simple reason that DenseNets does not learn feature maps, and consequently, these parameters are not needed. A number of ResNets variants have made a minor contribution; these layers can be removed, and the model's definition is shown in Figure 3.

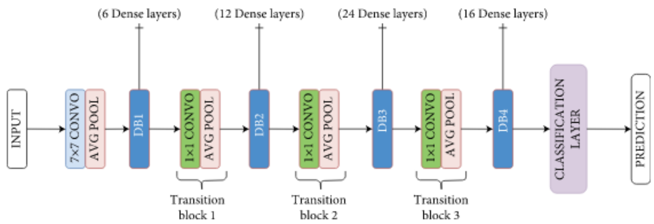

Figure 3: DenseNet121 architecture[18].

DenseNet layers are limited in scope with only a few extra filters and include only a small subset of key characteristics. Due to the fact that deep neural networks integrate both information flow and gradients, this issue manifests itself during the training phase of data. DenseNets solves these problems by using the actual input's gradients and transfer functions. Dense Net's network architecture becomes more hierarchical as input from the (i-1)th level of feature translation is passed on to the pth layer. Since DenseNet accepts input from any layer, including levels (i-1) and (i-n), it can be used for a wide variety of tasks (where n must be less than the number of layers total). The network is normalised using a batch normalisation step, which reduces the true error between data as significant variance is analysed[19].

V. Results and Discussion

Plant Village has compiled 54,303 images of leaves, both healthy as well as diseased, and divided them into 38 categories by species and condition. Sample images from the input dataset that were created using pre-processing methods are shown in Figures 4 and 5 below.

Figure 4. paper Bell Images.

Figure 5. Tomato Target Sopt.

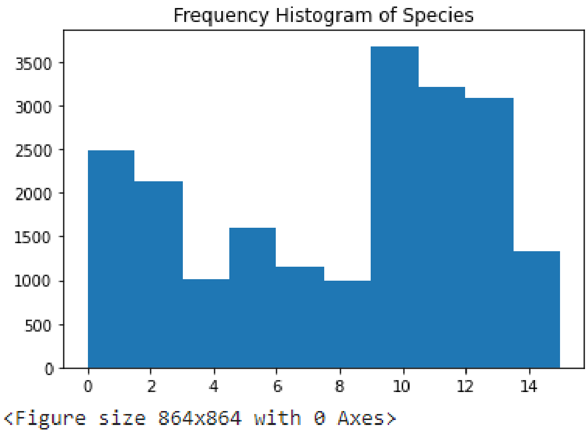

Figure 6. Histogram Plot of Classes.

A frequency distribution represents the rate at which each distinct value appears in a set of data. The histogram shown in Figure 6 is the most common type of graph used to show frequency distributions. In ecology, the phrase "frequency of occurrence" describes the proportion of plots that include a given species.

5.1 Performance Evaluation

A number of performance indicators will be used to assess the effectiveness of each classification model.

Accuracy: A classification model's precision reflects the system's overall efficacy and can be assessed using the technique described in:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision: The proportion of actual positive scores to projected positive scores indicates how accurate a classification model as well as method is. Here is the formula for determining precision:

$$Precision = \frac{True\ Positive}{(True\ Positive + False\ Positive)}$$

Recall: Performance in this metric is determined by how well a model can identify the true credible argument out of all observed true positive instances.

$$Recall = \frac{True\ Positive}{(True\ Positive + False\ Negative)}$$

F1-score: F1 is a measurement that considers both recall accuracy and sensitivity. Its value is a number between 0 and 1. If it has a value of one, the classification algorithm performed well; otherwise, if it has a value of zero, the classification method performed poorly.

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

5.2 Experiment Results

The outcomes of the experiment are displayed through numerous graphs, metrics, and tables. The following paragraphs feature a detailed discussion of the experiment's findings. This research presented a deep learning strategy utilizing DenseNet201 and Resnet101 for the purposes of categorization as well as feature extraction.

Table 1. Parameters Used

Input image	48*48*3
Neural Net	DenseNet121, ResNet101
Pooling	Global Average Pooling
Dropout	50%
Normalization	Batch Normalization
Optimizer	Adam
Learning rate	0.002
Loss	Categorical cross entropy
Metrics	Accuracy
Epoches	100

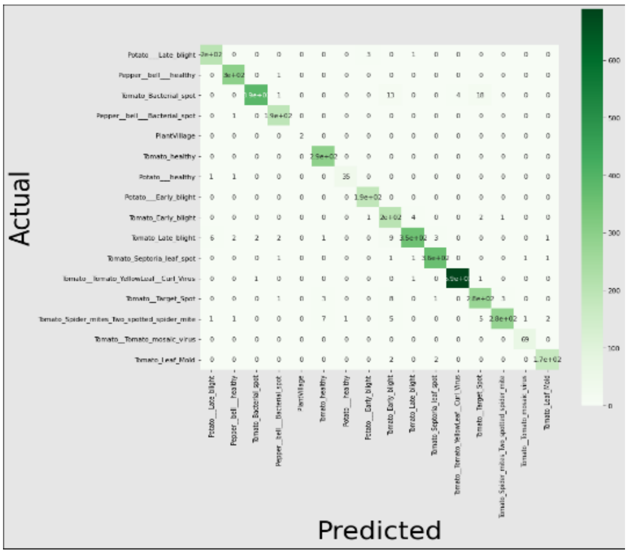

Figure 7. Confusion Matrix

Repeatedly, the DenseNet121 model's confusion matrix is displayed in Figure 7 above. The expected and actual labels for the data are shown on the x and y axes, respectively. The confusion matrix is used to assess the efficiency of a classification method.

Table 2. Assessing the Effectiveness of the Model

Model	Accuracy	Precision	Recall	F score
DenseNet121	98.37%	96%	98%	95%
ResNet101	95.90%	97%	98%	97%

VI. Conclusion

It is common practise for farmers to diagnose plant diseases before harvesting their crops. Careful handling is required because it is potentially toxic to vegetation. As a result, efficiency, output, and product quality are all impacted. The death of plants due to disease has a major effect on the economy. To efficiently scan large agricultural areas and detect early symptoms of disease, automated plant pathogens classification is crucial. Images can be used in the automated evaluation of computer vision algorithms. The model improves recognition accuracy and can adapt to different settings. While traditional methods require a larger and higher quality data set for the convolutional neural network, the model presented here achieves better results. It's possible that this method could aid farmers in the rapid diagnosis and treatment of plant diseases. The model that best handles the complexities of the environment may yield reliable identifications. There are challenges to be overcome, but the deep learning-based plant disease detection model proposed in this study has the potential to reduce environmental complexity and improve detection performance. As is made abundantly clear, the transfer learning approach is labor-intensive and necessitates frequent iterative calculation. In our future studies, we plan to develop a new neural network to generate zero-having started sets that are appropriate for the various leaves. This will allow us to shorten the training time, increase the transfer learning model's end of calculation threshold, and finish the iteration sooner.

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