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Recognition of Plant Diseases by Leaf Image Classification Based on Improved AlexNet

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Abstract: **If plants and crops suffer from pests, it impacts the country's agricultural production. Farmers or specialists usually observe naked-eye plants for disease detection and identification. But time-consuming, costly and incorrect may be this technique. Adequate and accurate findings are achieved using image processing methods. The main emphasis in this paper is on identifying plant diseases and reducing crop loss, therefore increasing the efficiency of production. Our suggested study identifies the symptoms of plants at a very early stage and uses a Deep Learning (DL) method to classify the plants' diseases based on their symptoms. This method adds to the conventional AlexNet the deconvolution layer to decrease the percentage of parameters and the cost of computation, classifying images with a fully connected layer. This research article presents a technique based on improved AlexNet for classification of plants. With a best accuracy of 96.5%, the suggested method identifies different diseases in plants with less complexity.**

Keywords: ***Plant Diseases, Deep CNN, plant disease, AlexNet, Leaf Image***

I. INTRODUCTION:

Farmers may choose different suitable crops and identify the appropriate pesticides for plants with wide diversity. Plant disease leads to substantial decreases in both agricultural product quality and quantity. Plant disease investigations are based on the study of clearly visible plant patterns. Monitoring plant health and disease serves a key role in effective agricultural cultivation. The expert in this area was first responsible for monitoring and analyzing plant diseases [1]. It takes huge effort and also considerable processing time. In the detection of plant diseases, image processing methods may be utilized. Disease symptoms are most often seen on the leaves, stems, and fruit. The disease-sensing plant leaves show the symptoms of the disease. Most diseases, however, produce a certain manifestation of the visible spectrum, such that the first method used in practice for plant disease detection is naked eye inspection by a trained expert [2, 3]. There was a mistake. A plant pathologist should have good monitoring capabilities to identify common symptoms to obtain exact identification of plant diseases. Symptom variations suggested by diseased plants may result in an incorrect diagnosis because hobbyists and amateur gardeners may have more difficulty.

To assist this, the requirement for a method that helps to detect plant diseases by taking into account the plant's appearance and its visual symptoms may assist amateur gardeners and skilled experts in the diagnosis of disease. Computer vision has received attention because of accurate plant disease diagnosis practices that will expand market growth in the field of precision agriculture [4-6]. Common processing technologies for digital images, such as color analysis and thresholding, have been utilized to identify and classify plant diseases. Therefore, the need for accurate and intelligent identification is of greater importance for all types of plant diseases. Deep learning technology has advanced further in recent years in the research of plant disease detection. Deep learning (DL) technology [7-9] is transparent to the user, plant protection researchers and statistics professionals are not high. Image characteristics and the classification of plant diseases can be automatically extracted [10], eliminating the traditional image recognition technology of feature extraction and classification design a great deal of work. These qualities make the technique of deep learning well recognized and a hot subject of study in plant disease. The overall goal of this study is to improve plant disease detection and rehabilitation by means of the CNN model with the Improved Alexnet.

II. Related Works:

Image processing technology in many areas, including automation, medicine, etc., has been utilized in recent years. In addition, image processing is also used to identify plant diseases via the conventional approach. Cameras, computers, and the required software are required for image processing systems. Plant pathologists want a precise and reliable diagnostic method for soybean plant conditions. In this research, they present an effective technique for identifying soybean diseases based on a transfer learning strategy via pretrained neural networks of AlexNet and GoogleNet (CNNs). In [11], the authors reported CNNs for AlexNet and GoogleNet trained to detect three soya diseases using image samples of 649 and 550 diseased and healthy soya leaves. The method presented leverages the 5-fold cross-validation approach and models known as AlexNet and GoogleNet have respectively attained an exactness of 98.75% and 96.25%. This accuracy was much greater than traditional pattern recognition methods. The testing findings for the detection of soya diseases have shown the greatest effectiveness in the suggested model.

The agriculture sector is the major industry in the national economy, ranging from the absorption of research to its performance as a foreign exchange contributor. Rice is a crop that is the staple diet of the majority of people. The availability and quality of rice are thus factors that have to be taken into account, whether for national or export quality consumption. It is intended to identify rice crop diseases that may lead to decreases in rice production or poor rice quality using a smart artificial method (by observing the leaves). In [12], the authors submitted CNN, the outcome of multilayer perception (MLP) development utilized for 2D data processing. The CNN technique includes a wide range of different layers, including the convolution layer, the sub-sample/pool layer and the FC layer. In this study, the best accuracy was found using several CNN architectures.

This study used four leaf disease types in rice plants for every disease type. However, the authors tried to achieve 91% accuracy with the help of an automatic plant disease detection mechanism. The proposed architecture predicted 4 types of diseases that are common in the rice crop. The system's best model has a configuration of 128:128:16:4-layer. Since many farmers live in distant parts of the nation, they are always suspecting whether or not their crops are healthy. This makes them a precautionary step that is harmful to their edible fitness using pesticides and artificial fertilizer. In [13], the authors sought to deal with this problem by using the cloud to identify whether the crop is healthy or diseased. Its goal is to classify images using supervised learning, along with clarifying the architecture of the system, utilizing Convolutional Neural Networks, which classify images of diseased plants. It emphasizes the need for data collection in real time. They also attempt to minimize this by comparing classification methods (CNN and SVM) and selecting the best algorithm to decrease the misclassification rate. The project data collection is collected on Indian farms. Lastly, the classification of leaf images has become a major concern that has to be solved since it enables individuals from many sectors of society to find appropriate solutions to various difficulties. The classification of clouds also results immediately. Because of their large datasets, even an RBF kernel does not help with the SVM to be non-linear and large datasets, CNNs have achieved higher classification results than SVM. This architecture may further be utilized across other plants by adding a couple of more layers to the architecture and adjusting the parameters in order to create a model for different plants and to give an accurate classification model.

Automatic detection utilizing image processing methods results in results quickly and accurately. The authors of [14] presented a method for the evolution of illness model identification by means of the use of deep convolutional networks, which promotes leaf picture categorization. Advances in computer vision provide an opportunity in the area of precision plant protection to be extended and improved, as well as in the market for computer vision applications. The truly unique training approach and the methodology employed enable a fast and simple deployment of the system in practice. The whole paper describes all the necessary stages for the implementation of this model of disease identification, from image collection to a database evaluated by specialists in agriculture, and a deep learning framework for the performance of deep CNN training. This technique is a novel strategy for the detection of plant illnesses via a deep-seated neural network that has been trained and tailored specifically for the plant leaf database which has been collected separately for various plant diseases. The advancement and uniqueness of the model that has been constructed is due to the ease of using the CNN model.

Since plants are exposed to many diseases, plant diseases may be monitored extremely expensively by experts in the agricultural area. A system is required that can identify diseases automatically. In [15], the authors developed a methodology that would classify leaf diseases and predict them in plants. This approach is built on a network that is a kind of deep learning. The data set used in this study was obtained from the Kaggle website (Plant Village). The data set includes 34,934 RGB images and 15 different classes of healthy and diseased plants using leaf images may be effectively classified using the deep CNN model. The model utilized data and dropout methods. In order to implement the CNN model suggested by Adam Optimization Technique, the Soft max output layer was utilized with a clear and concise cross-entropy loss function. The results achieved by the model presented in the training phase were 97.42% and in the test phase, 96.18%.

III. PROPOSED METHODOLOGY:

The whole process of building a model for recognition of plant diseases using deep CNN is further explained. The whole procedure is split into many essential phases in the following subsections, beginning with collecting images and training deep neural networks for the classification process. The framework consists of several steps to ensure that the disease depicted in figure 1 is identified accurately.

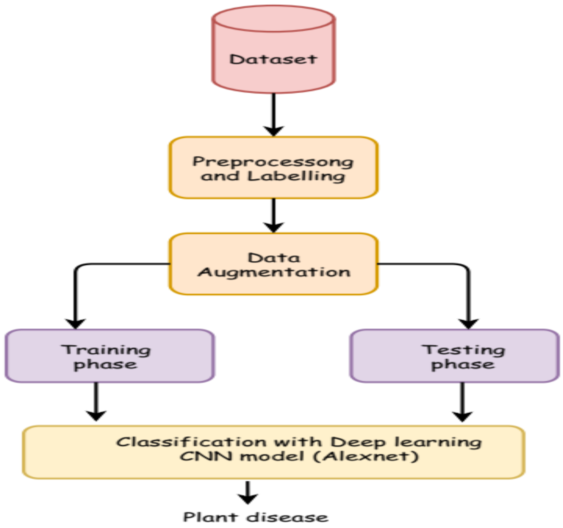


Figure 1: Overview of the Proposed Framework

A. Dataset:

The PlantVillage data collection (PVD) [14] is, to our best knowledge, the first public information collection for plant disease detection. The images in the PlantVillage collection are nevertheless obtained in laboratory settings and not in real conditions in cultivated areas, since their effectiveness in the real world is probably low. We instead collect images of healthy and diseased plants in real life in order to generate a data set which is publicly accessible.

B. Image Preprocessing and Labelling:

Final images designed to be utilized by the deep-neural network classifier have been pre-processed to achieve consistency for improved feature extraction [15]. In addition, image preprocessing required the manual process of getting cropped by considering regions of interest (ROI) on plant leaves. The images having resolution and dimension problems are treated during dataset collection as data set images. The dataset images have been scaled to 256×256 to reduce the training time.

C. Augmentation Process:

The primary aim of increasing the data is to increase it and to distort images, which contributes to minimizing overfitting throughout the training. Overfitting occurs in machine learning and that signifies a random noise . The increase included one of many methods of transformation, such as affinity transform, perspective transform, and basic image rotations. Affine transformations (linear transformations and vector addition) have been used to represent translation and rotation. A transformation matrix of 3 ×3 was necessary for the change of the perspective. Even after the change, the right lines would stay straight. Simple image rotations and rotations of various degrees were applied to varied degrees to the increase procedure.

D. Training and Testing Split:

Train the deep neural network to build a data-set model for image classification. The whole dataset is divided randomly into training and test sets. The training set for the model is utilized. Usually, these sets have to be partitioned into a ratio of 20% – 80%, 60% – 40%, 80% – 20%, etc. The most accurate results may be achieved if more images are included in the training data set. 80% of the data set is utilized for model training and 20% for testing in this study.

E. Classification:

The model is ready to classify any unlabeled images of plants after completion of the training process. The model takes the image as an input and compares the training and test imagery and provides the name of the plant as the output along with the name of the disease.

Improved AlexNet Image Classification Algorithm: As shown in Figure 2 above, it consists of 5 convolutional layers (CL) and 3 full connection layers (FL) that explicitly employ maximum pooling after 2 CLs. AlexNet has an 8-layer convolutional network.

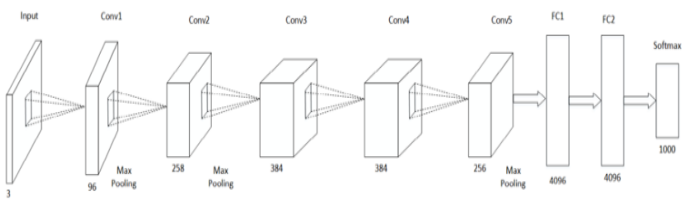


Figure 2: AlexNet model structure diagram.

Instead of conventional sigmoid and tanh functions, Alexnet utilizes ReLU as its activation function. ReLU with its activation feature enhances the model's training speed and regulates gradient loss not only effectively but also facilitates the formation of the depth of the network. Equation (1) shows the type of ReLU function:

$$\mathrm{ReLU}(x)=\max(0,x) \qquad (1)$$

AlexNet uses drop-out to decrease the level of excess fits. During the model training process, with a certain probability, the stopping process of neurons takes place, thereby reducing dependency on local nodes, and improving the model's capability to generalize. To extend the working performance, a deconvolution layer was appended to AlexNet based on the detailed analysis of the AlexNet model. The proposed network structure is illustrated in Figure 3.

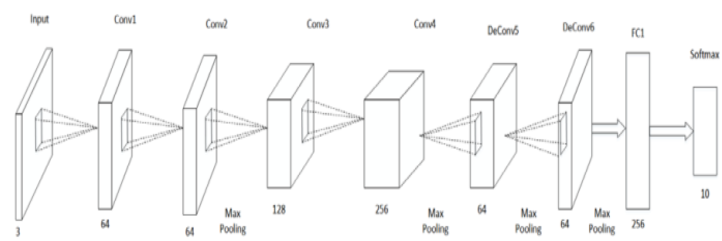


Figure 3: Improved AlexNet used in this paper

The network consists of four convolution layers, two deconvolutional layers and two full-connected layers. For feature extraction, a 3×3 convolution kernel is employed to prevent the missing of some particular features. Simultaneously, the overlapping maximum pooling is utilized to reduce the map size for data. The biggest distinction sandwiched between the traditional model and AlexNet is the incorporation of a deconvolution layer between the CL and the FC layers was introduced. With the help of the deconvolution process, the feature map number simplification makes FC layer input and node numbers greatly reduced. In a similar way, the FC layer parameter proportion gets reduced in the whole network. To decrease the model by overfitting, increase the penalty on the loss function to prevent parameters that are too big or too small to keep the model reasonably simple. If the loss function after regularization is K, then

$$K(\theta)=K(\theta)+\beta\lambda(\theta) \qquad (2)$$

the larger β is, the greater the penalty, and the larger the percentage of regularization as shown in the equation (2), $\beta \in [0, +\infty)$ if β is 0. The regularization of L2 in this study improves the ability to generalize a model and the weight of a model is reduced to approximately 0, as in equation (3):

$$K(\omega)=K(\omega)+\frac{1}{2}\beta\|\omega\|_2^2 \qquad (3)$$

After a convolutional layer, the batch normalization (BN) layer is added to undertake the task of data normalization process that is capable of speeding network convergence, in a similar fashion to addressing gradient loss and gradient explosion problems by introducing two parameters, γ and, α, as depicted in the formulation of equations (4) and (5) for feature distribution. The BN layer task is to obtain the input samples variance and mean for data standardization by incorporating 2 parameters such as: a mean sample, σ denotes sample variance, and denotes a constant that closely approaches 0.

$$\hat{} \qquad \sqrt{\sigma^2 + \delta} \qquad (4)$$

$$y_i = \gamma x_i + \alpha = BN_{\gamma,\alpha}(x_i) \qquad (5)$$

IV. Results and Discussion:

As a deep learning framework, we utilized Keras with a Tensorflow backend. The data given in this section pertains to training using both original and augmented images in the whole database. As we know, convolutional networks may learn features when trained on larger datasets, but original images are not used to evaluate results. Once the network parameters have been improved, 96,55% of the total accuracy has been achieved. In Figure 4, the leaf pictures sampled from the dataset are shown.

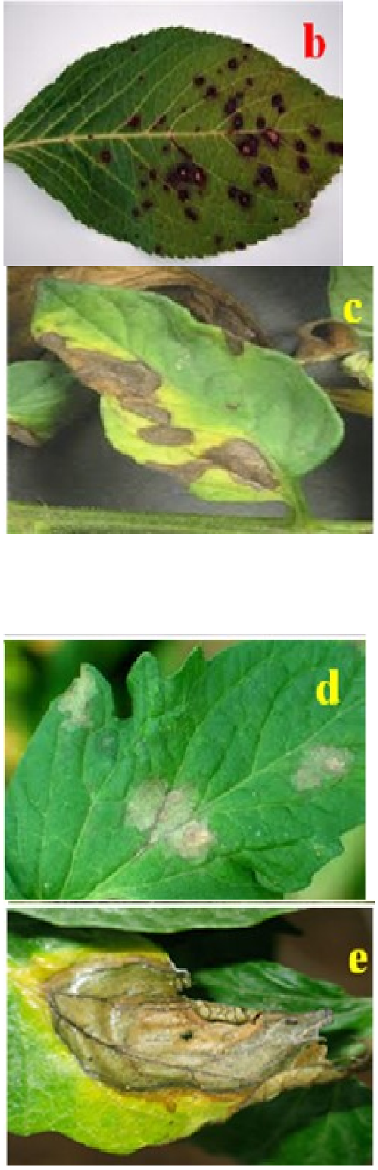


Figure 4: Diseased leaf images (a) Normal (b) Septoria (c) Early bight (d) Powder-mildew (e) Late blight

Transformations applied during the augmentation method are displayed in Figure 5, in which first row clearly shows affline transformation process (used for scaling) from a single image, the second row shows perspective transformation process, and the last row interpretations the image rotation process.

(a)

(b)

(c)

Figure 5: Process of leaf transformations: (a) affine transform; (b) perspective transform; (c) Leaf rotations

The model was trained separately by means of augmented and not-augmented hyper-parameter data sets. It demonstrates that the Deep CNN (Improved Alexnet) suggested model validation accuracy has been improved by utilizing the augmented image dataset.

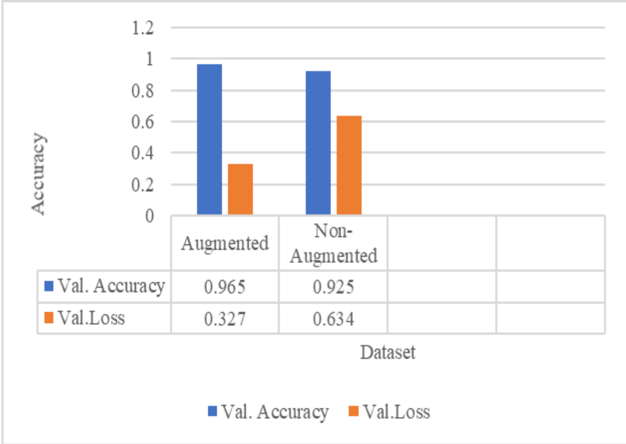
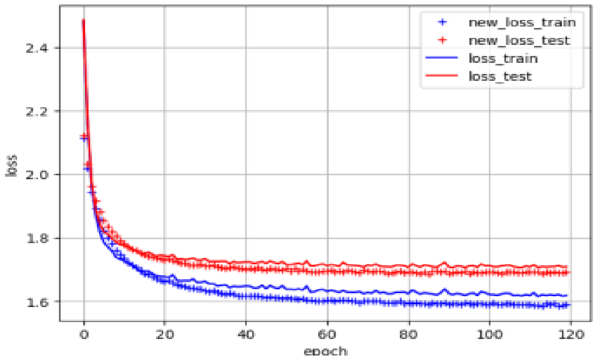
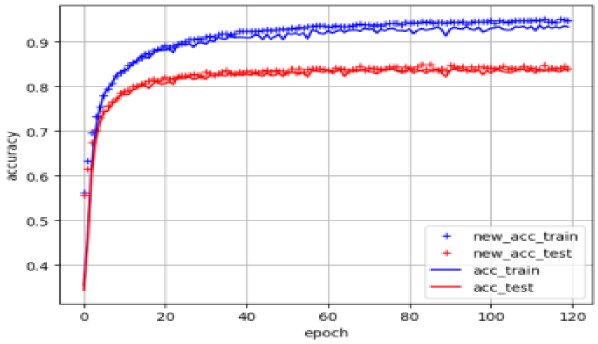


Figure 6: Validation accuracy of the augmented and non-augmented datasets



(a)



(b)

Figure 7: Comparison of Validation accuracy and loss functions of two models

Figure 7 shows the findings of the investigative simulation. From the experimental findings it is observed that the conventional AlexNet and Improved AlexNet appear in Figure 7(a) and Figure 7(b), when the feature map number is reduced. It can be observed that the accuracy has increased to some degree after the deconvolution layer has been included, and the accuracy of the test set is about 1% better.

V. CONCLUSION:

Deep learning is a new image processing and pattern recognition method for the recognition of plant leaf diseases, and it can successfully resolve the problems. In the suggested Deep CNN model, 38 different classes of healthy and diseased plants may be classified successfully by the use of images. Furthermore, the increase in data increases the amount of training data. In the classification of test set plant images, our proposed framework obtains an overall accuracy of 96.55%. On the basis of AlexNet, the deconvolutional layer is sandwiched between FC and CL respectively, that lowers the parameter percentage of the FC layer and simplifies the parameter number. In parallel, we use the kernel 1×1 for the network parameter reduction process to achieve the operation of increasing and decreasing dimension. New images from a variety of different plant sources, geographical regions, leaf growth, crop circumstances, image quality and modes will be collected to enhance the number of database classes and the size of the data database.

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