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Leaf Disease Detection Using Convolutional Neural Network

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Abstract: The field of agriculture greatly influences our lives. The most significant economic sector in our country is agriculture. A profit in agricultural products is the result of proper management. Farmers produce less because they lack knowledge about leaf disease. Since production determines both profit and loss, plant diseases of the leaves detection is crucial. The method for classifying and detecting leaf diseases is CNN. The primary goal of this study is to identify leaf diseases in tomato, potato, grape, apple, and corn plants. Plant leaf diseases are tracked over vast agricultural fields for the purpose of detecting crop diseases. As a result, certain disease features are automatically identified and treated accordingly. The suggested Deep CNN model has been contrasted with well-known transfer learning techniques like VGG16.

Keywords: CNN, VGG16, Agriculture, Leaf diseases.

I. INTRODUCTION

The production of food and rural livelihoods, as well as our economy, are significantly influenced by agriculture. Plant diseases, however, can negatively impact crop quality and productivity, especially if they damage leaves. That's why identifying leaf diseases is essential to preserving crop health and guaranteeing agricultural success. Technological advances, especially in the area of deep learning, present a promising solution, since farmers frequently lack the necessary expertise to correctly identify and manage these diseases.

In this case, diseases in the leaves of tomato, apple, grape, potato, and grain plants are identified using deep learning techniques, more especially Convolutional Neural Networks (CNNs). With this method, a large dataset comprising 31,119 photos of plant leaves that are divided into 24 different disease categories is analyzed. Many disease categories, including Apple scab, Black rot, and apple rust for apples, Black rot, Esca, and leaf blight for grapes, and comparable thorough classifications for corn, potato, and tomato plants, are painstakingly labeled throughout the dataset.

To properly build and assess the CNN models, the images are resized to 256 x 256 pixels and separated into training and testing sets. This technological intervention supports biological research and agricultural institutes in addition to helping farmers by offering an automated and accurate method for disease detection. The agricultural industry can improve crop monitoring procedures, lower disease-related losses, and eventually boost productivity and profitability by putting these cutting-edge detection techniques into practice.

(A). Apple scab Blight (B). Grape Esca (C).Corn leaf spot (D)Potato Early (E)Tomato Bacterial Spot

Fig 1. Leaves with Disease part

In fig.1 we can see vegetable and fruit leaves like potato, tomato, corn, apple, grape with diseased part this disease can be easily detected using deep learning techniques

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This study's main goal is to use convolutional neural networks (CNNs) to precisely identify leaf diseases in plants such as potato, tomato, corn, grape, and apple. CNNs are an advanced technique for analyzing a large dataset of 31,119 images that have been resized to 256 x 256 pixels for reliable training and testing. The CNNs distinguish between healthy and diseased leaves. Farmers and agricultural researchers can greatly benefit from the development of a dependable, automated system for plant leaf disease detection, which is the goal of this research.

The need to increase crop productivity and profitability by reducing losses due to disease is what inspired this study.Maintaining healthy crops requires accurate diagnosis and recognition of leaf diseases, and this technology offers farmers—who might not have specialized knowledge in plant pathology—an approachable solution. The automated disease detection system also provides a useful tool for early disease management, which benefits biological research and agricultural institutes. By putting such cutting-edge methods into practice, large farms can significantly enhance their monitoring procedures, guaranteeing prompt interventions and improved crop health overall.

II. LITERATURE SURVEY

[1] The creative smart farming system takes advantage of deep learning and cutting-edge infrastructure to improve tomato production both in terms of quality and quantity while tackling the inescapable problem of leaf diseases. This study, which focused on the Diamante Max breed of tomato plants, created an effective method for identifying plant diseases. To enable thorough disease detection, a motor-controlled image capturing box was built to take pictures of all four sides of each plant. The system uses a deep convolutional neural network that was trained on a dataset of diseased and healthy leaves in order to identify Phroma Rot, Leaf Miner, and Target Spot. The Transfer Learning disease recognition model attained 95.75% accuracy, while the F-RCNN anomaly detection model received a confidence score of 80%.

[2] The field of agriculture greatly influences our lives. The most significant economic sector in our country is agriculture. Farmers produce less because it is difficult for them to diagnose leaf diseases. However, agricultural scientists can see things more clearly and offer a better solution with the help of films and pictures of leaves in order to address the issue of crop disease. It is important to remember that there is a greater chance of poor nutrition if the crop is diseased and less productive. because of the advancements in technology, which have made devices capable of identifying and detecting plant diseases.Reduce the detrimental effects on harvest by identifying illnesses and treating them more quickly. In this paper focus on plant disease detection using image processing techniques [2]. This paper access open dataset images that consist 5000 images of healthy and diseased plant leaves, and there used semi supervised techniques for croptypes and detect the disease of four classes.

[3] This paper focuses on applying advanced deep learning techniques to detect five apple leaf diseases: brown spot, rust, mosaic, aria leaf spot, and grey spot. The study creates the INAR-SSD model by using the Apple Leaf Disease Dataset (ALDD) and utilizing image annotation and data augmentation technologies. This model achieves a high detection speed of 23.13 FPS and a detection performance of 78.80% by using the Google Net Inception structure and Rainbow concatenation. The findings show that, in comparison to earlier techniques, the INAR-SSD model offers an effective, real-time solution for the early diagnosis of apple leaf diseases, with improved accuracy and speed.

[4] This work uses a convolution neural network (CNN) with deep learning to identify plant leaf diseases. Training the Convolutional Neural Network Model with Over 39 Different Classes of Open Plant Leaf Disease Dataset and Background Images is done. That contain six types of data augmentation methods and that are used for gamma correction, image flipping, principal component analysis(PCA) color augmentation, rotation, noise injection, and scaling. Everyone is aware that data augmentation is being used. That may improve the model's performance. Various training ranges of epochs, batch sizes, and dropouts were used to train the model. The suggested model outperforms the other five transfer learning approaches when CNN is compared. when applying the data for validation. Despite this, the suggested model for simulation achieves a 96.46% classification accuracy. CNN accuracy is superior to transfer learning approaches accuracy.

[5] This paper contains vegetable, fruit, crops and flowers Agricultural Images, and that leaf disease. The agricultural product type associated disease identification. These diseases are specific to the product component which can be root, seed, and leaf. This is helpful into the provide identification of disease from remote lab. The work is here divided in two steps. In first step, the ring project-based segmentation model is defined to explore the features of leaf images. Once the features are identified then work is apply for PNN classifier to identify the existence disease . The work is about to identify the health and infected disease based on featured region identification. The work is applied on randomly collected leaf images from web for different plants.

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[6] Crop diseases have grown significantly in recent years due to severe climate change and weakened crop immunity. This results in widespread crop destruction, lower cultivation, and ultimately financial loss for farmers. The identification and treatment of diseases have become increasingly difficult as a result of the variety of diseases growing quickly and farmers not having enough knowledge about them. The texture and visual similarity of the leaves help identify the type of disease. Therefore, the solution to this issue lies in the application of deep learning to computer vision. This study suggests a deep learning-based model that is trained on a public dataset of pictures of crop leaves in both healthy and unhealthy conditions. The model serves its objective by classifying images of leaves into diseased category based on the pattern of defect.

[7] Agriculture has become far more than simply a method to feed ever growing populations . It's important wherever in additional than seventieth population of an Asian country is depends on agriculture. Which means it feeds nice range of individuals. The foremost necessary consider less amount crop of quality because of disease. Leaf disease detection may be stop agricultural losses. The aim of this is to develop a software system answer that mechanically find and classify disease. That consist steps like image acquisition, Pre-processing, Segmentation, extraction and classification are involves disease detection. The leaves images are used for detecting the plant diseases. Therefore, use of image process technique to find and classify diseases in agricultural.

[8] The Indian economy grows when agricultural productivity rises. This paper contributes to the identification of unhealthy leaf using image processing techniques in order to achieve an efficient and intelligent farming system. For this purpose, leaves from ladies finger plants are chosen, and they are examined to look for early symptoms of various diseases, such as leaf spot, powdery mildew, and yellow mosaic vein. A leaf image is taken, processed, segmented, features extracted, and classified to ascertain if it is healthy or unhealthy. Noisy picture data sets are also produced and taken into consideration due to practical restrictions in weather and other terrain regions. SVM and ANN are used for classification, while K-Means clustering is utilized for segmentation. PCA is used in this work to minimize the feature set.The findings indicate that SVM and ANN have average detection accuracy of 85% and 97%, respectively. They are found to be 92% and 98%, respectively, in the absence of noise. The agricultural industries will eventually be fully automated thanks to the efforts of this group.

[9] Plant diseases are a important in the crops production, which affects food security and reduces the profit of farmers. Identifying the diseases in plants is the key to avoiding losses by proper feeding 7 measures to cure the diseases early and avoiding the reduce in production. In this paper, the authors used two methods for identification and classification of healthy and diseased tomato leaves. In the first technique, the tomato leaf is classified as healthy or unhealthy using the k-nearest neighbor approach. Later, in the second technique, they classify the unhealthy tomato leaf using probabilistic neural network and the k-nearest neighbor approach. The features are like GLCM, Gabor, and color are used for classification purposes. Experimentation is conducted on the authors used that own dataset. That consist 600 healthy and diseased leaves. The experimentation reveals that the fusion approach with PNN classifier outperforms than other methods.

[10] A critical step in the application of machine learning for plant disease detection is the segmentation of diseased symptom regions in plant leaf images. The procedure referred to as Region of Interest (ROI) segmentation entails the separation of symptom lesions with only color variations from the surrounding green tissue, which is then used to extract discriminant features.Nevertheless, studies have demonstrated that a segmented ROI does not capture the rich anatomy of a disease's symptom progression from onset to manifestation, which is necessary for the cultivation of finer disease characterization dissimilarity features. Furthermore, a number of issues plague the typical ROI segmentation process, ranging from extrinsic factors like disease anatomy where symptoms fade into healthy green tissue, making the separation boundary impalpable, to intrinsic factors like image capture conditions. This makes the process even more complex or yields inaccurate results. This study suggests using color homogeneity thresholding to extend the border region to cover a portion of healthy tissue in order to automatically segment the extended region of interest (EROI) and incorporate information about the progression of symptoms. A well-known Plant Village dataset was used to test the usual ROI segmentation and reduced ROI in order to create a ground truth. From this dataset, distinct textural and color features were taken out and used to construct a linear classifier. An analysis of the classification outcomes further substantiated the benefits of the suggested methodology for extracting dissimilarity features. Finer characterization features can be extracted for plant disease classification and severity estimation through this research.

[11] Global food security has become a very important research focus. This is due to the fact that food is a basic need of human beings and its adequate supply to meet the need of humans must be ensured. However, been one of the major problems threatening the adequate supply of food to humans. The early detection of these diseases can assist in their efficient management, thus making huge differences between survival and destruction of crops in farmlands affected by

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these plant diseases. This has inspired increased research into the use of deep learning in the domains of image processing and computer vision. This paper presents a study on the use of deep learning-based approach to identify diseased plants using leaf images by transfer learning [16]. The study uses NAS-Net architecture for the convolution neural networks (CNN). The model is then trained and tested using a publicly available Plant Village project dataset that contains varied images of plant leaves with multiple variations in infection status and location in the plants. Using the model, an accuracy rate of 93.82% was achieved.

[12] In India, tomatoes are the most commonly used vegetable. A tomato is a great source of important minerals for overall health. India is the world's third-largest tomato-producing country. Plant production was impacted by the disease, accounting for 10–30% of the overall loss. It is crucial to identify these diseases in the plant in order to stop any significant losses. a suggested methodology that seeks to precisely identify and categorize tomato crop diseases. The most prevalent tomato plant diseases, including Septorial leaf spot, Bacterial leaf spot, and Yellow leaf curl, are included in the paper. The Plant Village dataset is used to analyze 54,306 photos of 14 crops that are afflicted with 26 different diseases. There are about 18160 photos of tomato leaf diseases in the subset. The three main components of the suggested methodology are, in general, data collection, pre-processing, and classification. The photographs utilized to carry out the suggested methodology were taken from the Plant Village dataset, which is openly accessible. The last stage involves classifying the input images using the LeNet, a slightly modified version of the standard deep learning convolutional neural network (CNN) model that has convolutional, activation, pooling, and fully connected layers. The accuracy of this suggested system is 95%.

III. IMPLEMENTATION

There are a total of 24 different types of labels for the leaves of apple, grape, potato, and tomato plants. apple label, specifically: healthy, black rot, rust, and scab. specifically, Corn Cercospora Corn rust, corn blight, gray spot, and healthy corn. specifically: Leaf blight, Black rot, Esca, and healthy on the grape label. specifically: healthy, late blight, and early blight on the potato label. The following conditions are listed on tomato labels: yellow leaf curl virus, target sport, spider mite, bacterial spot, early blight, healthy, late blight, leaf mold, and septoria leaf spot.31,119 photos of apples, corn, grapes, potatoes, and tomatoes make up the dataset; 24000 of those photos are used. All Images are resized into 256 x 256, that images divided into two parts training and testing dataset, the whole range of the train test split using 80-20 (80% of the whole dataset used for the training and 20% for the testing).

Classes	no. of images	used images
Apple_scab	1000	1000
Apple_black_rot	1000	1000
Apple_cedar_apple_rust	1000	1000
Apple_healthy	1645	1000
Corn_gray_leaf_spot	1000	1000
Corn_common_rust	1192	1000
Corn_northern_leaf_blight	1000	1000
Corn_healthy	1162	1000
Grape_black_rot	1180	1000
Grape_black_measles	1383	1000
Grape_leaf_blight	1076	1000
Grape_healthy	1000	1000
Potato_early_blight	1000	1000
Potato_healthy	1000	1000
Potato_late_blight	1000	1000
Tomato_bacterial_spot	2127	1000
Tomato_early_blight	1591	1000
Tomato_healthy	1909	1000
Tomato_late_blight	1000	1000
Tomato_leaf_mold	1000	1000
Tomato_septoria_leaf_spot	1707	1000
Tomato_spider_mites_two-spotted_spider_mite	1676	1000
Tomato_target_spot	1404	1000
Tomato_mosaic_virus	1000	1000
Total images	30052	24000

Table 1. Leaf disease dataset

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The work related to leaf disease detection using CNN show to detect and classify leaf disease using image processing techniques that follow steps like

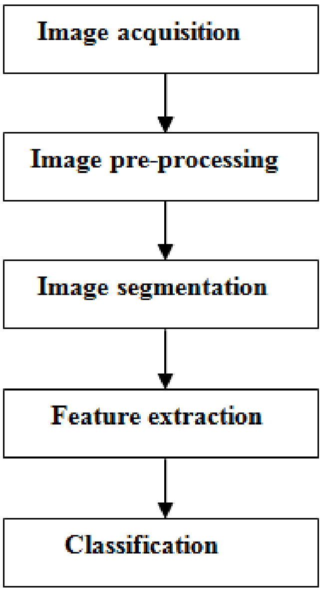

Fig 2. General Block Diagram of Feature Based Approach

A. Image Acquisition: image acquisition in the first load the image in digital picture process and that consist capturing the image through digital camera and stores it in digital media for additional MATLAB operations.
B. Image Preprocessing: The main aim of image pre-processing is to enhance the image information contained unwanted distortions or to reinforce some image features for any processing. Preprocessing technique uses various techniques like dynamic image size and form, filtering of noise, image conversion, enhancing image and morphological operations.
C. Image Segmentation: In image segmentation is used K-means cluster technique for partitioning of pictures into clusters during which a minimum of one part of cluster contain image with major space of unhealthy part. The k means cluster algorithmic rule is applied to classify the objects into K variety of categories per set of features.
D. Feature extraction: After clusters are formed texture features are extracted using GLCM(Gray-Level Co-occurrence Matrix).
E. Classification: In classification is used for testing the leaf disease. The Random Forest classifier is used for classification.

A computational model that works can be created using convolutional neural networks (CNN). On the inputs of unstructured images and transforms them into labels of matching classification outputs. They fall under the class of multi-layer neural networks, which are capable of being trained to acquire the characteristics needed for classification.
Compared to traditional methods, less pre-processing is needed, and automatic feature extraction improves performance.

The best outcomes for leaf disease detection could be obtained by utilizing a LeNet architecture variation. Convolutional, activation, max-pooling, and fully connected layers are also included in LeNet. LeNet is an elementary CNN model. This architecture is employed in the LeNet model [13] for the classification of leaf diseases. Compared to the original LeNet architecture, it has an extra block of convolution, activation, and pooling layers. Figure 2 illustrates the model that was used in this paper. A convolution, an activation layer, and a max pooling layer make up each block. This architecture uses three of these blocks, followed by fully connected layers and soft-max activation. Fully connected layers are used for classification, while convolution and pooling layers are used for feature extraction. The network can be made non-linear by using activation layers.

Convolution operation is applied by the convolution layer to extract features. As the depth increases, The extracted features become more complex. The number of filters increases gradually as we move from one block to the next, but the size of the filter remains fixed at 5 × 5. In the first convolution block, there are 20 filters; in the second and third, there are 50 and 80 filters, respectively. Because pooling layers are used in each of the blocks, the size of the feature maps is reduced, which necessitates this increase in the number of filters.

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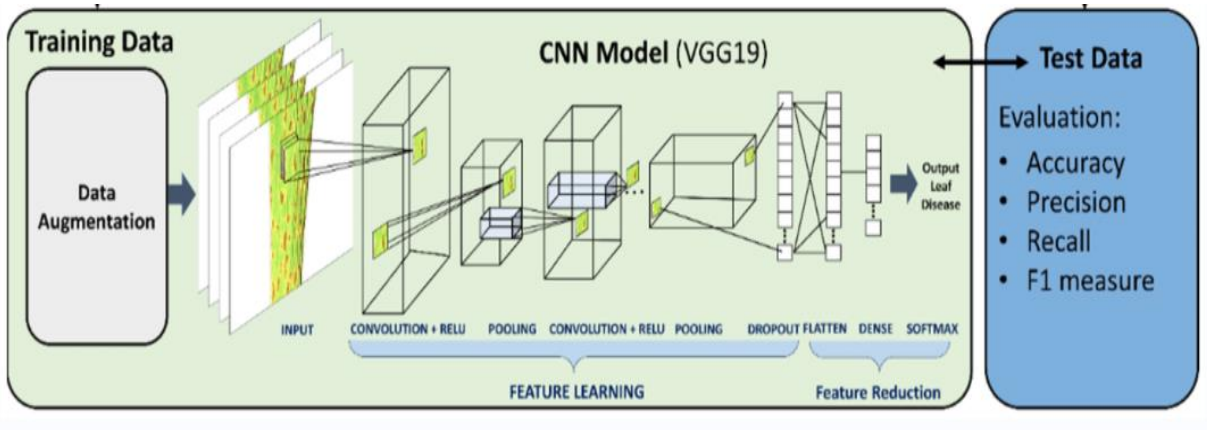
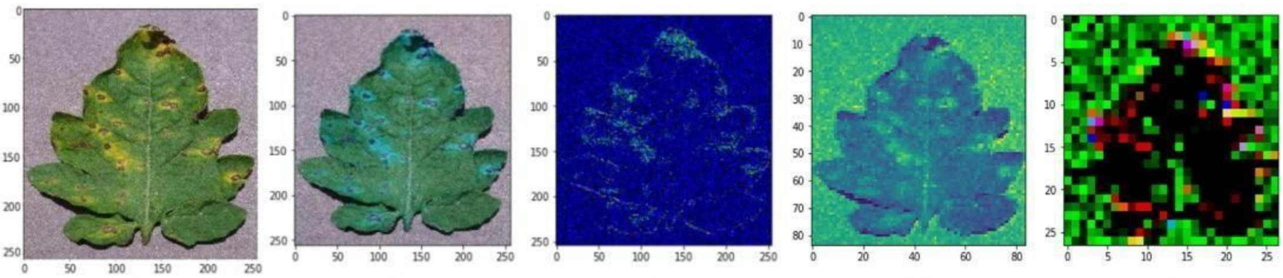


Fig 3. Proposed Workflow.

To maintain the dimensions of the image, feature maps are zero padded following the convolution operation.By using the max pooling layer, the size of the feature maps is reduced, which expedites the training process and lessens the model's sensitivity to small input changes. For max pooling, the kernel size is 2×2. Each block introduces non-linearity through the use of the Re-LU activation layer. In order to prevent the train set from being over fit, the Dropout regularization technique has also been applied with a keep probability of 0.5. During training iterations, dropout regularization arbitrarily removes neurons from the network to lower model variance and make the network simpler, which helps avoid over fitting. Ultimately, the two sets of fully connected neural network layers that make up the classification block have 500 and 10 neurons apiece. The second dense layer is followed by a soft max activation function to compute the probability scores for the ten classes.



(a) (b) (c) (d) (e)

input image convolution layer-1 convolution layer-2 convolution layer-3 flatting layer

Fig 4. Experimental result

Further, in every experiment, the overall accuracy over the whole period of training and testing regular intervals (for every epoch) will be computed. The overall accuracy score will be used for performance evaluation. Transfer learning is a knowledge- sharing method that reduces the size of the training data, contains 224*224 image fix size. To transfer the learning of a pre-trained model to a new model Transfer learning is useful. Transfer learning has been used in various applications, such as plant classification, software defect prediction, activity recognition and sentiment classification. In this, the performance of the proposed Deep CNN model has been compared with popular transfer learning approach VGG16.

A convolutional neural network is called VGG16. The convolution layer receives a fixed RGB image size of 224 x 224 as input. Convolutional layers receive the image and apply filters with a very small receptive field, the smallest size that can capture the concept of left, right, up, and down, center: 3×3 [18]. Using 1×1 convolution filters in certain configurations allows for a linear transformation to occur after the input channels' non-linearity [18]. One pixel is the fixed convolution stride. The convolution layer input spatial padding ensures that the spatial resolution is maintained post-convolution; for 3x3 convolution layers, this means that the padding is 1 pixel. Five max-pooling layers—which do not always follow convolution layers—performed spatial pooling after some of the convolution layers. Max-pooling is done over a 2x2 pixel grid.

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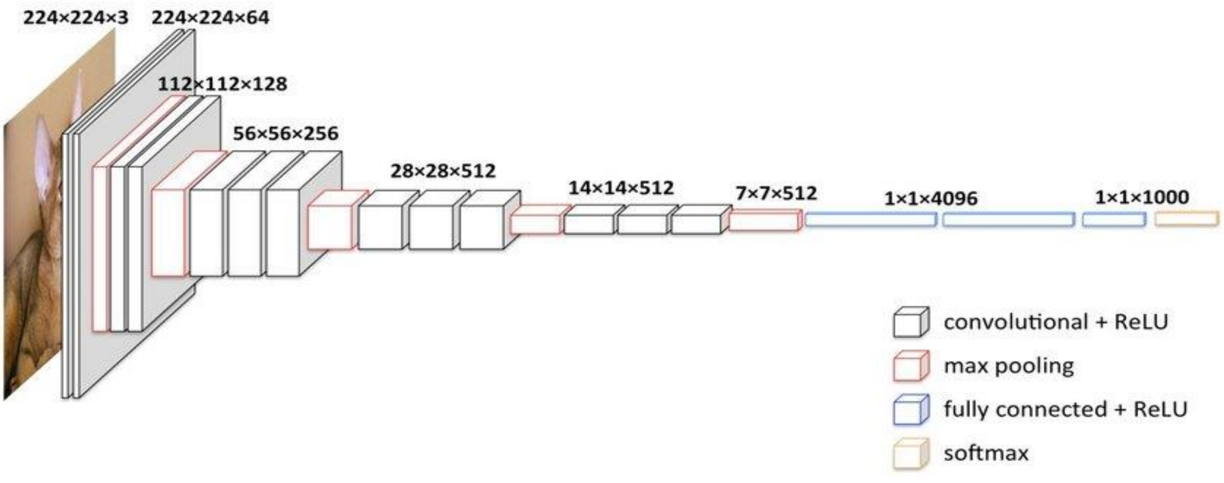

Fig 5. VGG16 architecture

A stack of convolutional layers is followed by three layers. The first two have 4096 channels, while the third has 1000 channels because it uses 1000-way ILSVRC classification. The softmax layer is the last layer. The leaf disease is identified by the fully connected layer configuration. Every concealed layer has the ability to be corrected. Re-Lu It should be noted that none of the networks have Local Response Normalization (LRN), which would enhance dataset performance, and that the rectified linear unit contains nonlinearity on the network.

IV. RESULT

Results show that leaf disease detection in agricultural plants like apple, corn, grape, potato, and tomato can be improved and automated with the use of deep learning techniques, particularly CNN models and transfer learning. Using sophisticated image preprocessing, segmentation, feature extraction (using GLCM), and classification steps, the CNN model based on the LeNet architecture achieved notable disease identification accuracy using a dataset of 31,119 images across 24 disease labels.

Additionally, incorporating transfer learning from the VGG16 model significantly increased accuracy, raising it to a remarkable 90.23%. With convolutional, activation, max-pooling, and fully connected layers efficiently extracting features and enabling precise disease classification, the experimental workflow demonstrated the capability of CNNs in handling complex image data. These findings demonstrate how deep learning techniques have the power to transform agricultural practices by automating and enhancing the early detection and management of plant diseases, which will improve crop productivity and health.

Epochs	CNN Accuracy	VGG16 Accuracy
150	90.229166 %	51.166334 %
120	86. 666667%	50.140005 %
90	86.133333 %	47.157776 %
60	85.085556 %	46.872223 %
30	84.166664 %	45.708333 %

Table 2. Comparison table of CNN vs. VGG16

V. CONCLUSION

In our study, we compare a CNN-based system for leaf disease detection with a conventional feature-based method, and we find that CNNs achieve a higher accuracy of 90.23%. Although VGG16 was also tested, CNN proved to be the more useful model for our needs. In the future, adding more leaf classes and disease types to the dataset will increase system resilience.

Accuracy and generalization can be increased even more by investigating sophisticated CNN architectures like ResNet or DenseNet and fine-tuning hyper-parameters. Farmers can be empowered with proactive disease management strategies by utilizing machine learning for predictive analytics and integrating real-time monitoring via IoT or drones for continuous field surveillance.

Developing scalable and workable solutions to maximize crop health and productivity in agriculture requires constant innovation.

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