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A Modified Deep Learning Model for an Early Stage Detection of Foliar Disease & Estimation of Damage Ratio in Maize Crop

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ABSTRACT
The plant diseases and crop infestation are prime factors responsible for low crop productivity. An early stage detection and estimation of quantum of plant disease in agricultural crop is always of prime importance for maintaining crop health. An automated plant health monitoring of crop can help in preventing major yield losses. The agricultural crops are susceptible to diseases due to multiple reasons and demands proactive early diagnosis and treatment. Machine Learning and Deep Learning models can be very effective to address such problems and can be used to develop automatic plant disease detection systems. The paper presents a modified Deep Learning algorithm for identification of plant disease in maize crop. Further the severity is estimated in terms of damage ratio. This may help to estimate crop yield and shall benefit the farmers to take timely corrective measures. In order to assess the intensity of infection and damage caused, image analysis is performed on the input image of diseased plant leaves. The Maize plant leaf dataset comprising of more than 4000 images is used for training the developed model. The dataset includes three primary diseases that affect Maize crops: Northern Leaf Blight, Common Rust, and Gray Leaf Spot. The modified algorithm uses VGG_19 model comprising of 19 network layers and best combination of hyper parameters such as number of epoch, batch size, learning rate etc are chosen to achieve high accuracy. Accuracy, Precision and Sensitivity are the three parameters used to evaluate the performance of proposed model. A comparative study is undertaken and reported in the paper. The developed Deep Learning Model has achieved a classification accuracy of 99% for disease detection and thereafter such a model is a strong contender to be used for an early stage plant disease detection technique.

Keywords: Agriculture, Deep Learning, Threshold, epoch, Batch Normalization, VGG 19.

I. INTRODUCTION

Plant diseases are a major threat to crop yields at the global scale and can cause huge financial loss to small scale farmers whose livelihood depends upon agriculture production. As per the reports, more than 50% of yield loss results from plant diseases and pathogens [1]. Plant diseases have a great potential to impact product quality, quantity, and production and can seriously harm crops. Plant diseases results in underdeveloped growth of plant causing adverse effects on productivity and requires timely actions to prevent crop failure. Major goal in agriculture is to achieve maximum yield with minimum investment while maintaining a good quality of the crop produce. Crop infestation due to diseases causes crop yield losses. An early detection of crop infestations followed by instant remedial and correcting measures to counter the factors can minimize yield losses. The problem of efficient and early plant disease detection is the major area of interest and requires great attention to improve the crop yields. Thus this marks an important action to detect plant disease at an early stage and take timely actions [2]. If diseases are detected in time, an appropriate remedy can be applied to minimize the yield losses. Manual plant disease detection by pathologist makes a diagnosis dependency on pathologist's observation skills and knowledge. Also manual disease detection process is time consuming, possesses limitations and does not provide satisfying outcomes. All these problems make an excellent area for use of computer based smart and automated diagnosis systems for plant disease detection [3]. Advancement in artificial intelligence technologies have paved the way for development of automated systems that can get faster and more accurate results in diagnosis of diseases in plants. One of the key sign of a plant disease is change in the plant's appearance, shape and color. Diseases primarily express themselves on the visible spectrum, and in such cases advanced detection models can be effective to automatically detect these manifestations [4]. Automatic plant disease detection is helpful because it reduces the efforts of manual disease monitoring and detects symptoms on plant leaves precisely at a very early stage. It is very important to continuously monitor plant health condition and detect the damage at early stages, which further facilitates decision making process and timely remedial actions for farmers. Automatic plant disease detection will facilitate those having no skills to identify disease characteristic symptoms and no access to pathological support infrastructure. Many cloud IOT based techniques have been developed to check soil heath [5], crop monitoring etc using sensors and other detection hardware [6]. But in the current scenario of digital era, automatic and handy devices using Machine Learning and Deep Learning software algorithms are required to perform plant health monitoring. Conventional machine learning algorithms have been used in numerous researches to perform plant health monitoring, but new developments in deep learning have led to deep learning models demonstrating remarkably effective outcomes in object detection, recognition, and classification. Therefore, DL based solutions are developing and strongly advised in agricultural research. The most promising method for automatically collecting discriminative features and doing classification is deep learning-based approaches. [7]. Sadojevic et al. (2016) developed a Caffe framework-based deep CNN-based approach for identifying plant diseases. The algorithm was able to achieve an average accuracy of 96.3 % when tested on different plant types [8]. Author suggested an image segmentation algorithm to automate plant disease diagnosis approach, and the algorithm was evaluated on 10 distinct plants. The genetic algorithm utilized in the suggested strategy yielded a high accuracy of 96% [9]. Lu, Y. et al. (2017) developed a model to identify damaged rice plants and offered a deep classification technique. 500 images were used to train the classifier on 10 prevalent rice diseases [10]. H. Ali et.al (2017) proposed the research study technique that used color histogram and textural data to identify diseases using the E color difference, attaining an overall accuracy of 99.9%. The team used a range of classifiers, including bagged trees, fine KNN, Cubic SVM, and boosted trees. The bagged tree classifier generated the most accurate results, with 99.5 %, 100 %%, and 100 % accuracy for the RGB, HSV, and LBP features, respectively. The Fine KNN, Cubic SVM, and Boosted tree classifiers had accuracy rates of 88.9 %, 90.1%, and 50.90 %, respectively [11]. Selvaraj et. al. provided a novel method to apply deep learning to detect signs of disease and pest in bananas. Using author-taken field images taken in real-time, the accuracy was over 90%. Several models were used, including ResNet50, InceptionV2, and MobileNet V1 [12]. Mohameth et al. offered an analysis utilizing deep learning feature extraction techniques to compare several CNN architectures. SVM and KNN classifiers were used in comparison studies [13]. As a backend for the Android application, Patil et al. (2019) proposed the notion of predicting plant disease using a deep convolution network (ResNet Architecture) for picture processing and classification. The application gathers the network's processed output results and provides crucial data, such as the pesticide's name, dosage, etc., for use in treating the identified disease. The proposed method had an 88.98% accuracy rate [14]. Atila et al. (2020) implemented EfficientNet deep learning architecture to classify plant diseases, and the model's performance was compared to that of other deep learning models already in use. Models were trained using a sizable dataset that included 61,486 enhanced images and 55,448 original images. The author tried a transfer learning strategy in which all model layers were made trainable. When utilizing the original dataset, the accuracy and precision were 99.91 % and 98.42 %, respectively. When using the enhanced dataset, the accuracy and precision were 99.97 % and 99.39 % [15]. Hassan et al. (2021) proposed deep convolutional-neural-network models, which are utilized to identify and diagnose issues in plants from their leaves because CNNs have shown remarkable achievements in the field of machine vision. The implemented models achieved accuracy of 98.42 %, 99.11 %, 97.02 %, and 99.56 % using Inception V3, InceptionReNetV2, MobileNetV2, and EfficientNetB0. In this work, depth separable convolution was employed rather than standard convolution, which resulted in a decrease in the number of parameters and processing time [16]. Zand et al. proposed the CNN technique using Multi Activation Function (MAF) module for optimization to detect disease in maize leaves. ResNet50 gave best results with 97.4% of accuracy to identify diseases in maize leaf dataset, and have 2.3 % improved result than the existing methods [17]. Malliga et al. proposed a method based on Deep CNN to identify diseases in maize crop. A Deep CNN was utilized to identify and categories the diseases in maize leaves. To improve the detection's precision, Alex Net architecture was also used. While Alex Net architecture achieved accuracy of 98.5 %, CNN only achieves accuracy of 87.5% [18, 19]. All the research performed to identify plant disease detection clearly shows that deep learning proves to have high potential in solving classification problems and is thus the same is chosen as the basic method in present research work. Diseased Maize image dataset comprising of 4188 images is chosen for classification algorithm. Image dataset comprises of healthy leaf images and diseased leaf images of three very common maize diseases i.e. Northern Leaf Blight, Gray Leaf Spot, and Common Rust. The algorithm aims to predict the disease class accurately and further utilizes morphological image analysis method to calculate disease severity in selected sample.

II. PLANT DISEASE DETECTION AND CALCULATION OF DAMAGE RATIO: SYSTEM MODEL

The Plant disease detection model illustrated in figure 1 explains the process chain of disease detection in maize plant. It explains how an input image gets progressed through model network and produced classification result. A test image of maize plant, infected with disease is passed to the model for classification. The input image enters to the VGG 19 model. It is a popular model known for its deep layers performing exceptionally well in image classification problems. During training phase, the model is trained with training dataset and its parameters are tuned to achieve optimized results. To improve the accuracy of the model, batch normalization technique is adopted to increase depth of model by adding additional layers to the model. Optimizer used for the model is Stochastic Descent Gradient, which performs computation at fast speed.

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The VGG 19 model consists of four layers: the convolution layer, the Relu layer, the pooling layer, and the fully connected layer. The convolution layer, an essential structure, applies a convolution filter to the image in order to find properties in it. To extract visual data, the filter separates the image into small regions called as receptive fields. The filter multiplies its elements by receptive field elements and convolves with pictures using predetermined weights. By swiping a filter with the same set of weights across the image, convolution processes with the ability to share weight can extract visual information. Relu layers are activation functions that are employed to alleviate the problems caused by over fitting. The pooling layer known as Max Pool, which is next to Relu, steadily reduces the size of the image while keeping just the most important elements. Once the features are extracted, fully connected layers are used for classification. Finally soft max function present at network end produced the predictions of class to which input test image actually belongs.

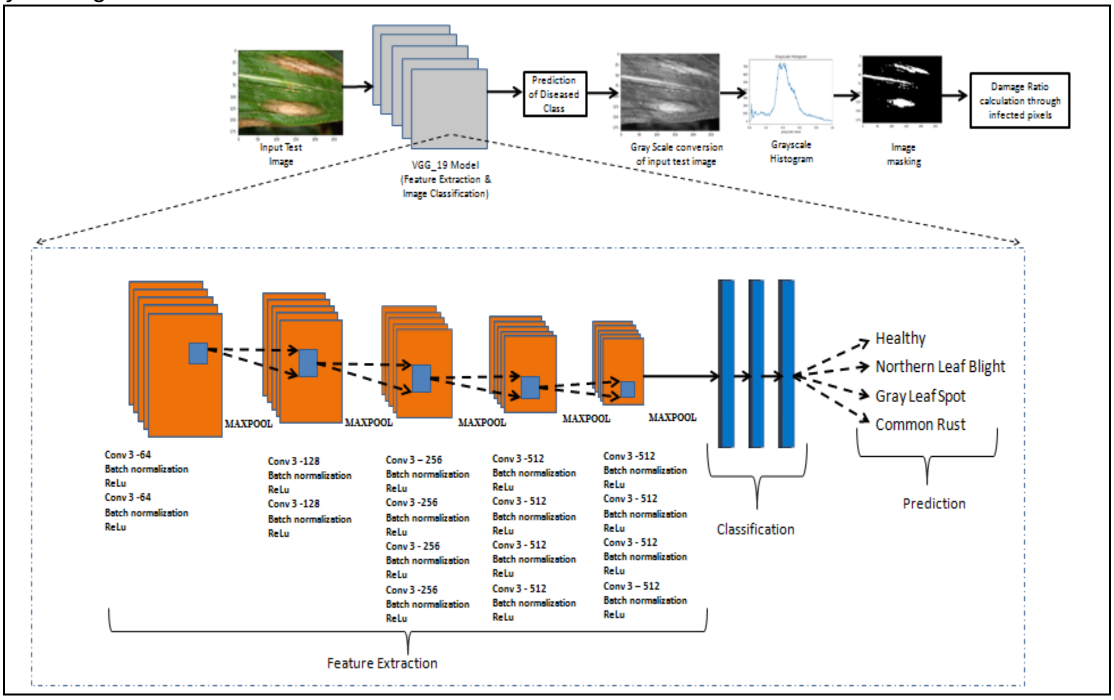

Figure 1: System Model

Now when predictions are made, morpho metric image analysis is performed on the classified test image. Image is first converted into a gray scale image and then a gray scale histogram is produced to identify threshold value. This threshold value helps to mask the desired infected area of leaf for calculation of damage ratio.

III. Materials and Methods

The proposed system model utilizes VGG_19 neural network architecture to classify the disease in the maize leaf, and the morphological threshold technique to estimate the severity of the disease. The framework shown in Figure 2, consists of range of operations i.e. 1) Input image dataset collection, 2) hyper parameter tuning, 3) Model training, 4) Classification 5) Image gray scaling, 6) Threshold Identification7) Disease Severity Calculation. The deep learning model used in this study is VGG_19.

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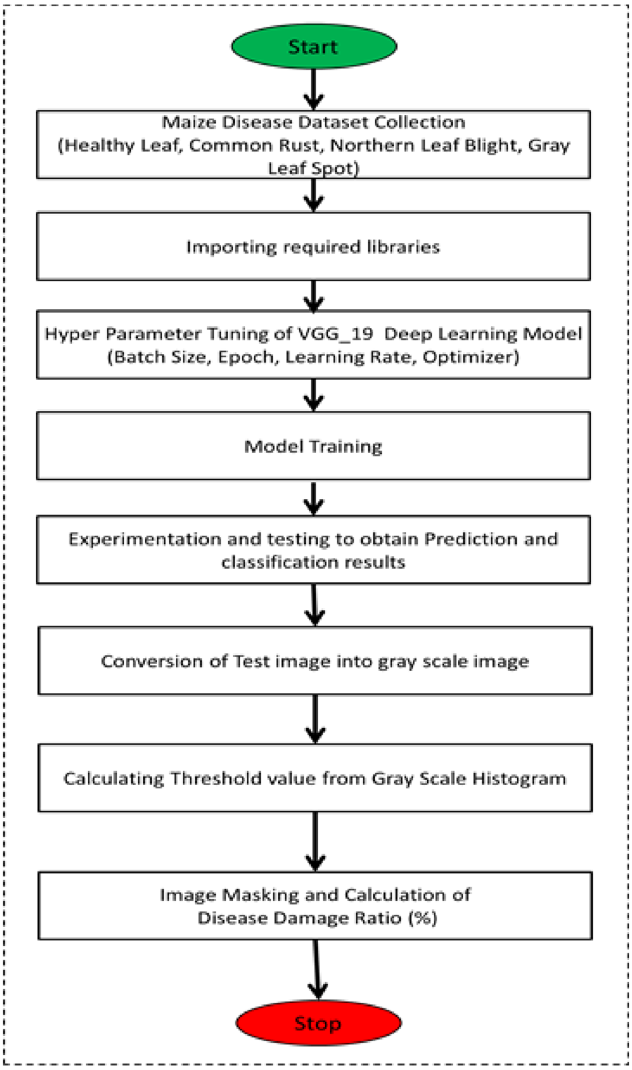

Figure 2: Process Flow of implemented model

VGG_19 Model Architecture

The term VGG stands for Visual Geometry Group, deep neural network architecture. The architecture possesses 19 weight layers. The model is used for various image recognition applications. As depicted in Figure 3, out of 19 weight layers, model possesses 16 convolution layers and 3 fully connected layers. The architecture comprises of weight matrix called filters which slides over input image to extract features. Filter gets convolved with input image to produce a feature map. The VGG_19 model uses 3*3 filters [20]. The movement of weight matrix is defined by the term stride. Stride numbers shows jump with which weight matrix slides on input image. Padding is also an important terminology used to maintain the dimensions of input and output equal, by adding zeroes to input matrix. Stride and padding of VGG_19 is 1.

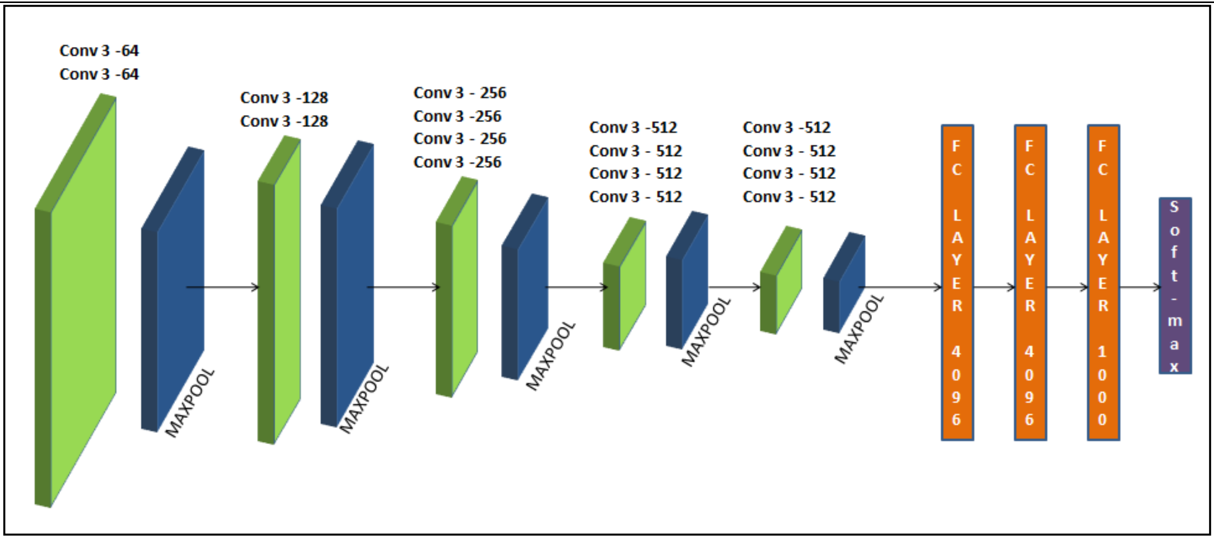

Figure 3: VGG _19 Architecture

As shown in Figure 3, VGG_19 comprises of different layers i.e. Convolution layers, Maxpool Layer, Fully Connected Layer and soft-max function. In order to identify characteristics in an image, the convolution layer, a crucial building block of deep learning networks, applies a convolution filter on the image. The filter divides the image into tiny parts known as receptive fields in order to retrieve visual information. The filter uses specified weights to convolve with images and multiply its elements by receptive field elements [21]. Next to convolution layer is maxpool layer which is a pooling layer. Pooling layers causes a progressive reduction in image size while retaining just the most crucial details. It compiles adjacent receptive field information and outputs the prevailing response. Once the features have been extracted, fully connected layers are used to classify the images [21], [22]. Convolution and pooling layers reduce, filter, and correct flattened picture pixels before they are supplied into the fully linked layers at the network's end. Applying a softmax function to the fully connected layers' outputs to complete them produces the likelihood of the class to which the input image belongs [22], [23].

Dataset Collection

Input dataset of 4800 images was taken to train the model. Dataset comprises of four different categories of maize plant leaf i.e. healthy leaf images and leaf images diseased with Northern Leaf Blight, Common Rust and Gray Leaf Spot. Images were downloaded from Kaggle website. Kaggle is a public online dataset repository containing various datasets to be used for Machine Learning experiments [24].

Hyper Parameter tuning

The process of selecting the ideal mix of hyper parameters to enhance the model performance is known as hyper parameter tuning. Hyper parameters are chosen and declared before model training. It operates by conducting numerous trials within a single training procedure. Every trial entails the full execution of your training application with the values of the selected hyper parameters set within the predetermined bounds. Once this procedure is complete, hyper parameter values are set to make model perform at its best [25]. It takes knowledge and a lot of trial and error to set the hyper-parameters. Learning rate, batch size, epoch and optimizer are some of the common hyper parameters employed in the experiment. The batch size is a hyper parameter that specifies how many samples must be processed before the internal model parameters are updated. Epoch is also an important hyper parameter that determines how frequently the learning algorithm iterates through the whole training dataset. Learning rate plays an important vital role in deep learning model training. The Learning rate, instructs a computer how quickly or slowly to reach a conclusion. A model's learning rate is crucial and varies depending on the application. A quick learning algorithm can overlook a few correlations or data points that might improve understanding of the data. Failure to do so will eventually result in incorrect classifications. Summary of the hyper parameters used is:

Parameter	Value

Batch Size	4
Epoch	10
Learning Rate	0.01
Optimizer	Stochastic Gradient Descent

Optimization

The Stochastic Gradient Descent (SGD) method is used by the model to improve categorization. Each cycle involves random data shuffles to approach minima depending on the batch size chosen. In order to reach the local minima, SGD performs more iteration. The duration of the computation grows as the number of iterations increases [26]. However, even when the number of repetitions is increased, the computing cost is still lower.

Batch Normalization

Batch normalization is the process of adding additional layers to a deep neural network to make it faster and more reliable. The input of a layer coming from a previous layer is standardized and normalized by the new layer. The Batch normalization expedites training by normalizing the hidden layer activation. It fixes the internal covariate shift issue. The loss function is smoothed using batch normalization, which increases the model's training efficiency by improving the model's parameters [27].

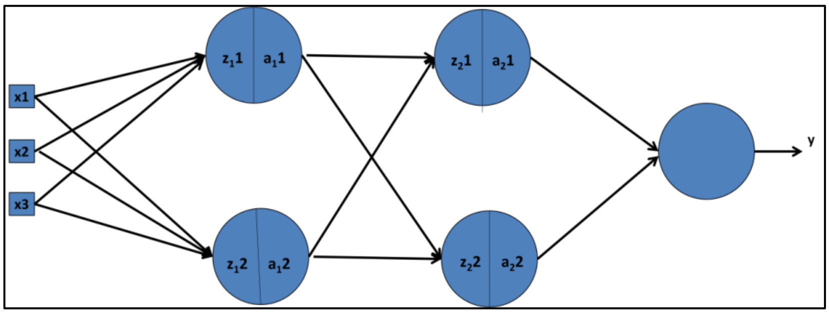

Figure 4: Concept of Batch Normalization

As seen in Figure 4, Batch normalized output for the network is computed by [26]:

$$Z^N = \left(\frac{z - m_z}{s_z}\right) . \gamma + \beta$$

Where the learning parameters of the Batch Norm are γ and β, and m_z and s_z are the mean and standard deviation of the output of the neurons, respectively. The mean and standard deviation are shifted by the parameters γ and β, respectively. A distribution with a mean of β and a standard deviation of γ is the output of Batch Norm over a layer. These values are learned over epochs along with other learning parameters like neuron weights, which work to reduce model loss [28].

Damage Severity Calculation

Northern Leaf Blight, Gray Leaf Spot and Common Rust are the primary foliar diseases affecting Maize Crop. The diseases show various symptoms on leaf surface, and each of them differ in terms of shape, color etc. Damage caused by each of them depends on various factors and requires a proper damage check to prevent the crop failure. Estimating damage severity in the leaf is an important aspect to forecast the yield loss. Damage check may aid in taking prompt remedial actions and save the crop against more infestation. Morpho metric technique is used to analyze the disease symptoms and calculate ratio of infected pixel in diseased leaf.

Two terms make up the phrase 'morpho metric', where 'morpho' refers to shape and 'metric' to measurement.It refers to the quantitative examination of form, a term that includes both size and shape. Morphometrics involves counting the number of objects in an image, determining their sizes, or determining their shapes. The individual "picture elements," also referred to as pixels, that make up images are stored as rectangular arrays of hundreds, thousands, or millions of pixels. Figure 5 illustrates the technique which involves conversion of RGB image to a Gray Scale Image, followed by image masking using the gray scale threshold value. A gray scale histogram is analyzed to obtain the threshold value for masking. This helps in differentiating infected area in leaf. Finally the diseased area is calculated by below formula [29]:

Damage ratio: $\left(\frac{\text{number of white color pixel}}{\text{Total image pixel}}\right) * 100$

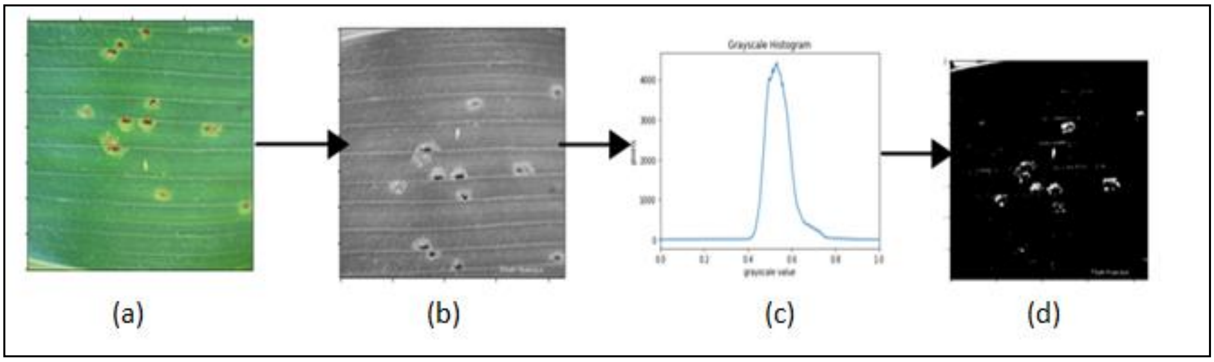

Figure5: Morpho metric analysis for a diseased leaf taken as input.(a) Colored Input Image, (b) Gray Scale Input image, (c) Gray Scale Histogram (d) Masked Image

To check the accuracy of the developed model, 116 test instances were performed by applying different input images to the trained model for predictions. Testing images used were not known by the model, and was not used during model training. Model could make 112 predictions correctly and has given 4 wrong predictions. Test Accuracy, Sensitivity and Precision are metrics used to check the classification performance. All these metrics are computed by four parameters: True Positive (TP): Diseased leaf is identified as diseased; True Negative (TN): Healthy leaf is identified as Healthy; False Positive (FP): Diseased Leaf is identified as wrong diseased; False Negative (FN): Healthy Leaf is identified diseased.

Test Accuracy: The %age of accurate predictions made using the test data is known as accuracy. It is computed by the formula [230]:

$$\frac{TP + TN}{TP + FP + TN + FN}$$

Test Sensitivity: The parameter used to assess a model's capacity to forecast the true positives of each available category is known as sensitivity. It is computed by the formula [30]:

$$\frac{TP}{TP + FN}$$

Test Precision: Precision is the percentage of instances that are truly relevant (also known as true positives) out of all the examples that were predicted to fall into a particular class. It is computed by the formula [30]:

$$\frac{TP}{TP + FP}$$

IV. RESULTS AND DISCUSSION

Input dataset are categorized into four classes, i.e. Northern Leaf Blight, Gray Leaf Spot, Common Rust and Healthy Leaf which are given as input to the VGG_19 model. Figure 6 illustrates the sample of images used for training:

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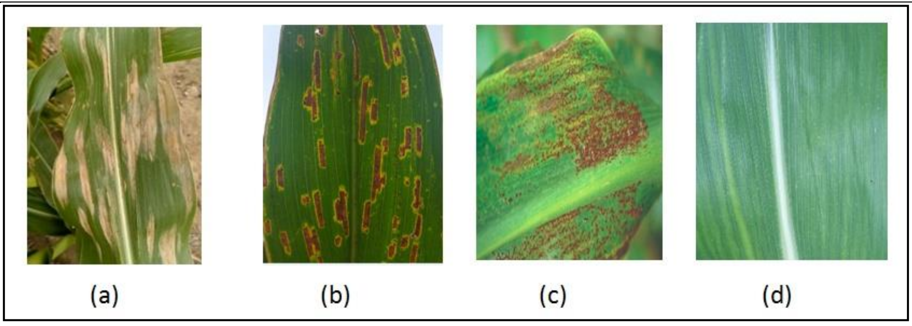

Figure 6: Input dataset sample images (a) Northern Leaf Blight (b) Gray Leaf Spot (c) Common Rust (d) Healthy [22]

All the diseases show different symptoms each varying in color, shape and size. More than 4000 images are taken for training and model is checked for 116 test instances. The dataset makes the model learn about the features, which facilitates the classification at later stage. The achieved results are as follows.

Training and Validation Accuracy: Training and validation accuracy are the metrics used to measure the performance of model. It helps to assess the quality of model during training. Training and Validation accuracy plots are represented as function of epoch numbers. Figure 7 shows Training and Validation accuracy achieved during experiment is 99.28% and 97.1 % for epoch 10 and 99.28 % and 97.9 for epoch 5 respectively. Epoch indicates training the network with all training data for one cycle. Training and Validation Accuracy increases with increase in number of epoch.

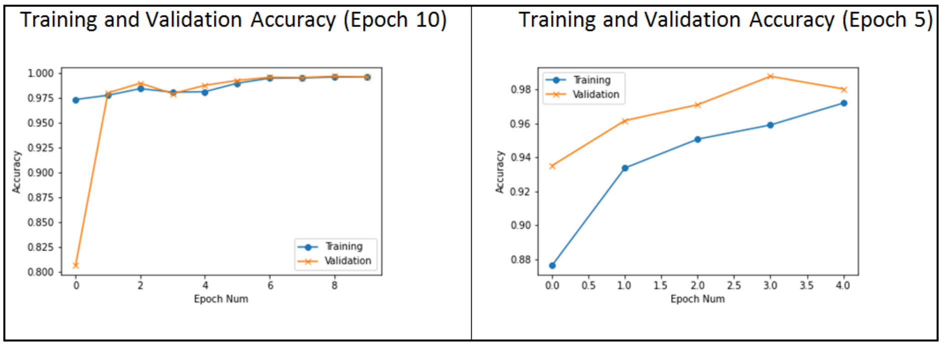

Figure 7: Training and Validation Accuracy graph

Training and Validation Losses : Loss plots are also represented as function of epoch number. The Loss plots reflect the error values generated between predictions and true values. A good loss curve is seen as a decreasing exponent getting flattened eventually, which is produced by Epoch value 10 in the performed experiment. Figure 8 shows Training and Validation loss achieved is 1 and 8 % for epoch 10 and 1% and 6 % for epoch 5 respectively. Training and Validation loss decreases with increase in number of epoch.

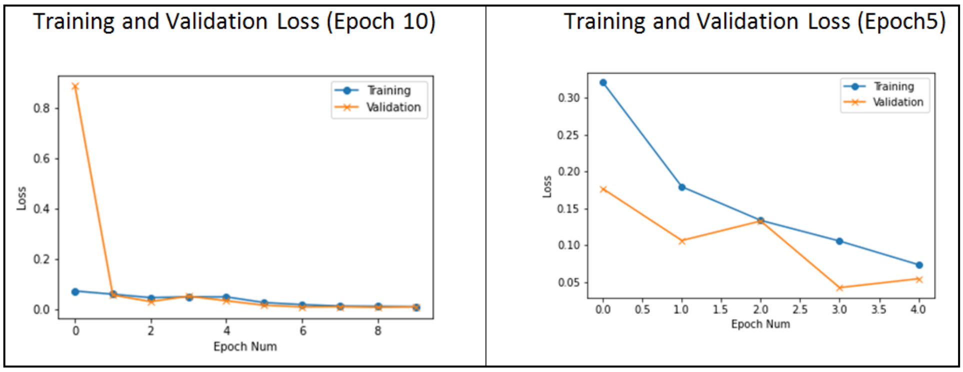

Figure 8: Training and Validation Loss graph

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Models like ResNet50, DenseNet161, Google Net and Alex Net have been used earlier by many researchers for plant disease detection. Model classification accuracy is therefore compared with other deep learning models, where it is discovered that the developed model has achieved the highest accuracy of 99.2823 %. Figure 9 shows the values of classification accuracy achieved by other models.

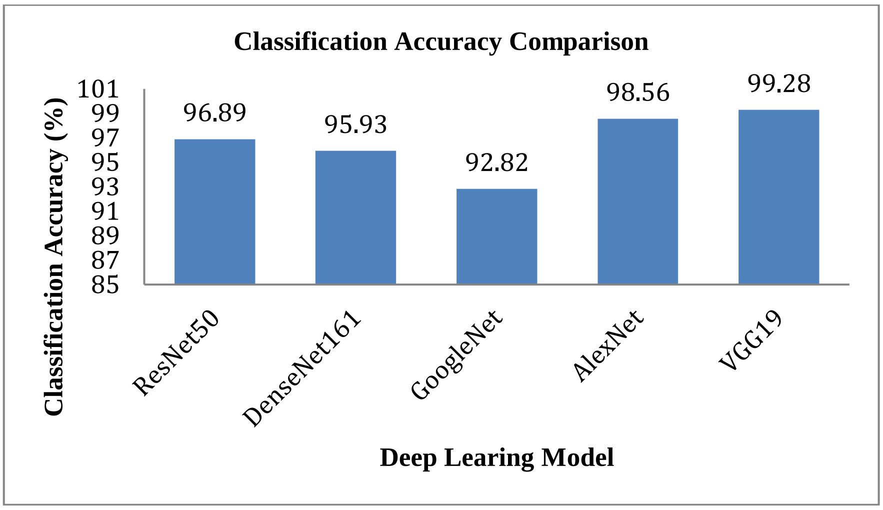

Figure 9: Deep Learning Model Comparison graph

Performance of the developed model is tested by simulating 116 test instances. Images belonging to all the four classes were used for testing and out of 116 images 4 images were identified incorrectly by the model. Further, True positives and True Negatives are calculated, to compute the Accuracy, Sensitivity and Precision of the model. The developed model framework is also compared against other Neural Networks i.e. Feed Forward Neural Network (FFNN), Recurrent Neural Network (RNN), Back Propagation Neural Network (BPNN), Deep Belief Network (DNN) and Convolution Neural Network CNN [30]. Comparison Table 1 mentioned below shows that the developed model has achieved highest results. Increasing the depth of model with the use of batch normalization has helped to achieve high accuracy, sensitivity and precision than other existing techniques.

Table 1: Comparison of developed model with existing Techniques

Classifier	Accuracy (%)	Sensitivity (%)	Precision (%)
FFNN	91.56	65.886	63.936
BPNN	91.306	67.286	66.916
RNN	91.436	72.36	67.486
CNN	91.616	82.186	72.046
DBN	91.956	83.826	77.4546
Deep Learning Model (VGG_19)	**96.55**	**100**	**96.03**

The maximum levels of accuracy, sensitivity, and precision were reached for the developed model, at 96.55 %, 100 %, and 96.03 %, respectively. In comparison to other neural networks, feature extraction and classification is found improved in the developed model. The graphical analysis of the different neural network framework is presented in figure 10. The graph shows that developed model has achieved precision value of 96.03 % which is higher than other networks and shows that increasing depth of layers improves the classification performance of neural network.

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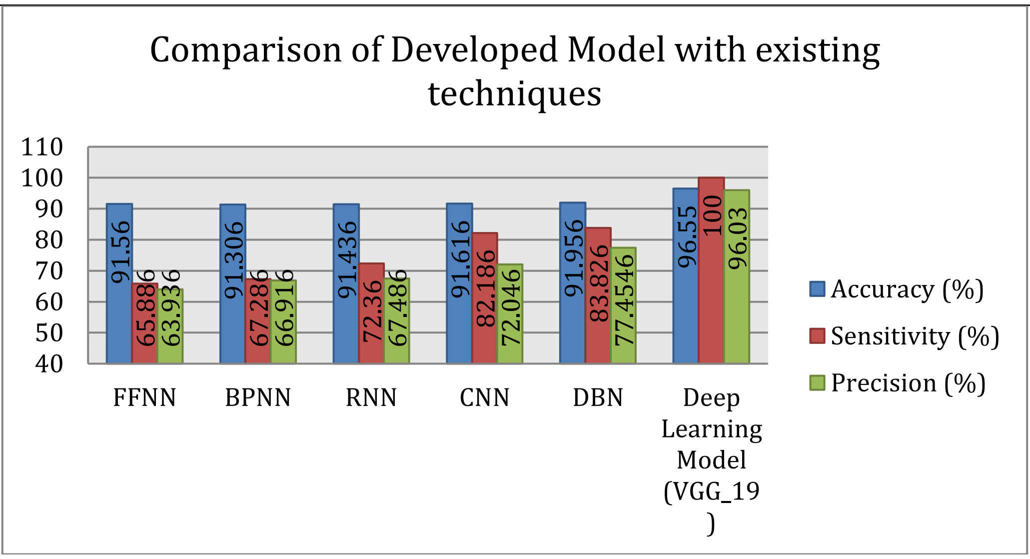

Figure 10: Comparison of Developed Model with existing techniques

V. CONCLUSION

The present research work draws some important conclusions for plant disease detection systems from the obtained results. It is found that the developed model (VGG 19) has given high accuracy and classification results to detect foliar diseases in Maize crop. The system model precisely studies the disease features and symptoms to classify the caused infections in plant leaf. With the optimum choice of hyper parameters, model could learn better and gave accurate predictions of the input class. Further it is evident from achieved results that increasing depth of layer using Batch normalization improves the model accuracy up to 99%. The paper also gives an insight to calculate severity of the damaged leaf on basis of pixel count calculation, which is a novel approach and has not been attempted in any research work to the best of our Knowledge. The developed model can be used in various software and mobile applications for early disease detection in plants. It is therefore concluded that the developed plant disease detection system shall help farmers to monitor their crops efficiently. It will eventually facilitate decision making process and help farmers to take timely corrective measures to prevent crop failure.

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