DEEP LEARNING-ASSISTED CLASSIFICATION OF CORN LEAF DISEASES

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ABSTRACT

As a source of food for people, livestock feed, biofuel, and a raw material for a variety of goods, maize is one of the most significant and widely grown edible agriculture crops in the world. A significant issue with food crops is natural disease detection and control.The quick detection of plant diseases is time-consuming and exceedingly challenging to small-scale farmers. Traditional methods and tools are not very effective because they require a lot of manual labour and time. Rapid disease detection is essential for treating illnesses successfully so that pesticides can be packed in time to control spread. This paper suggests an efficient image classification model based on enhanced deep-learning for precisely identifying three prevalent diseases of maize leaves.The suggested model uses Xception model ,which uses instances where transfer learning is employed and pre-trained Xception models are used for feature extraction. The deep features are combined to provide a more complex feature set, from which the model may get further insight into the dataset. With less computational cost and capacity to capture important characteristics, this depth wise separable (Convolutional neural networks) CNN gives better efficiency. The findings from this study are compared with other CNN such as EfficientNetB0 and DenseNet121. The proposed model achieves an accuracy of 99.40%, demonstrating its superiority. In this study, it is shown that suggested model provides better accuracy and is capable of diagnosing of corn leaf diseases.

Keywords – Plant disease, Diagnose, Diseased corn leaves, Convolutional neural networks, Deep learning architecture, Image classification, computational cost, Transfer learning, feature extraction.

I.INTRODCUTION

As the world population is predicted to approach 9.7 billion people in the coming years [6] sufficient food production will be a huge problem. In consequence of the country's fast population [6] expansion and escalating food consumption, increased crop yield is required. Due to plant diseases there is a deleterious effect on overall crop yield [4]and increase food scarcity [6]. $60 billion is the projected annual crop loss worldwide as a result of plant disease.

Global food [18] security is threatened by plant diseases [17]. The safety of the world's food supply depends up on the quality of crop [3]. Currently, maize is the food crop with the largest global yields [4], a substantial food source and a key industrial raw resource. Food security [3], the growth in farmer incomes, and the health of the country's economy all depend critically on corn production. Corn productivity and quality are directly impacted by diseases. More than

a dozen prevalent diseases affect maize, with the majority attacking the plant's leaves, ears and roots. Leaf damage is frequent among them. In this paper we have considered 3 corn leaf diseases. They are:

Northern Leaf Blight: The fungus Exserohilum turcicum is the source of this disease, which results in cigar-shaped leaf lesions and can lead to leaf blight. Infections that are severe can lower output and quality.

Gray leaf spot: It is caused by the fungus Cercospora zeae-maydis. Grey leaf spot is characterized by tiny, rectangular lesions on the leaves that can range in colour from grey to tan. Grey leaf spots may reduce yield if neglected.

Common rust: The fungus Puccinia sorghi is the cause of common rust, commonly referred to as corn rust. Small, round to elongated pustules on the leaves and husk of the maize plant are its symptoms. These spore-filled pustules are generally orange to reddish-brown in colour.

In order to control the illnesses and prevent the maize plant from being affected, these leaf diseases must be identified at the early stages of the corn plant's growth. Traditional methods of physically identifying corn plant diseases in agriculture fields need experts to conduct visual inspections, followed by diagnosis in laboratories. This process has following disadvantages:

1. Requires an extensive amount of time.
2. Might not consistently be accessible to small-scale agricultural producers.
3. Primarily requires agricultural experts.

This method has a number of shortcomings, thus for the intelligent diagnosis of these illnesses, deep learning [11] technology combined with image processing could be used. As, computer data processing capabilities advancing day-by-day automated and intelligent plant sickness detection, applications can be created using artificial intelligence, machine learning, and deep learning methodologies. In this study, a unique classification technique is proposed to accurately identify healthy maize leaves, common rust, northern leaf blight, and grey leaf spot in digital images. In order to integrate the prediction power of the models and create a classification model, this study used pre-trained convolutional neural networks (CNNs) [2], including the EfficientNetB0[7] CNN, DenseNet121 CNN [10], MobileNet, and Xception [9] models with appropriate parameter ranges and compared their accuracy and performances to suggest the best suitable model. The following concise statement sums up the primary goals of our work:

- more accurate classification with a manageable amount of parameters.
- Create a model for recognizing and detecting illnesses in maize plants by extensive testing and evaluation of the suggested model in contrast to other models.

II. LITERATURE SURVEY

In [22], a novel method for classifying leaf images using deep convolutional networks for plant disease identification was developed. With the capacity to differentiate between plant leaves and their surroundings, the created model can identify 13 distinct forms of plant illnesses from healthy leaves. The deep CNN training was carried out using Caffe, a deep learning framework . For distinct class tests, the experimental findings using the constructed model had an average precision of 96.3%, ranging from 91% to 98%.

The authors of [15] created three convolutional layers, three max-pooling layers, and two fully linked layers to make up the CNN. The constructed model achieved a classification accuracy of 94% on the subset of the Plan Village dataset that contained maize leaves with three diseases: corn grey leaf spot, corn common rust, corn northern leaf blight, and a healthy class.

In [24], For categorizing four kinds of maize leaves from the Plan Village dataset, the authors suggested a dense-optimized CNN. Five dense blocks made up the network, which was then followed by a SoftMax classifier layer. For the four classes used in the experiment, the CNN had a classification accuracy of 98.06% following training.

In [23] their study states that diseases in our crops are caused by a huge variety of plant pathogens, with a few hundred nucleotides to higher plants. Their impacts might range from minor symptoms to crises that completely devastate vast regions that were cultivated with food crops. The current shortage of food supply, which leaves at least 800 million people underfed, is made worse by disastrous plant disease. Plant diseases are challenging to eradicate because of their population genotypic distributions. It is to be understood that plant diseases pose a threat to our food sources.

The authors of [25] proposed a multi-context fusion network that would be used to combine contextual and visual data. The background knowledge included environmental aspects of the plant (such as temperature and humidity), which may cause or contribute to particular illnesses. The network attained a classification accuracy of 97.50% thanks to the categorization of these parameters, which boosted the identification phase.

In [12], the authors suggested a CNN approach for identifying maize leaf disease by augmenting the training set with more data and utilizing transfer learning to increase the CNN model's precision. On a portion of the Plant Village dataset that included four kinds of maize leaves (corn grey leaf spot, corn common rust, corn northern leaf blight, and healthy leaves), the optimized CNN displayed an average accuracy of 97.6%.

In [16] Utilising computer vision techniques makes it possible to automate this process, which is crucial for agricultural applications. In this study, the effectiveness of three cutting-edge convolutional neural network architectures for categorising maize leaf diseases is evaluated. They have used improvement techniques including data augmentation, Bayesian hyperparameter optimisation, and fine-tuning tactics. The maize leaf pictures from the PlantVillage dataset were used to assess these CNNs, and all experiments were verified using a five-fold cross-validation process over the training and test sets. The association between the maize leaf classes and the effect of data augmentation in pre-trained models is one of their results. According to the findings, 97% of the CNN models tested were accurate in classifying maize leaf disease.

In [8],a brand-new database named "ImageNet" has been unveiled; it is a sizable ontology of pictures constructed around the WordNet framework. The bulk of WordNet's 80,000 synsets will be filled with an average of 500–1000 crisp, full-resolution pictures thanks to ImageNet. Their research provides a thorough examination of ImageNet in its present configuration, which consists of 12 subtrees, 5247 synsets, and 3.2 million total pictures. It demonstrates how much more accurate and diverse ImageNet is compared to the existing picture databases.Through three straightforward applications in object identification, picture classification, and autonomous object clustering, they demonstrate the value of ImageNet. ImageNet's size, precision, variety, and hierarchical structure can provide computer vision researchers with unmatched opportunity.

III. METHODOLOGY

A. DATASET DESCRIPTION

The dataset utilized in this experiment consists of several extensive photographs of maize leaves captured at different phases of growth and in varied environment. There are 13,345 photos in total, divided into different categories that show both photographs of healthy and ill maize leaves. It consists of pictures of corn leaves divided into four separate categories: healthy maize leaves, common rust-infected leaves, grey leaf spot, and northern leaf blight. Fig. 1, displays a couple of sample pictures from each category in the dataset. Table 1 includes the number of photos in each category. The dataset is intended to assist in the development and evaluation of deep learning models for tasks involving the categorization of maize leaves.

Category	Training Images	Testing Images
Northern leaf blight	3119	429
Common rust	3286	396
Gray leaf spot	2255	374
Healthy	3068	418
Total	11728	1617

Table 1. Number of images in each category of the dataset.

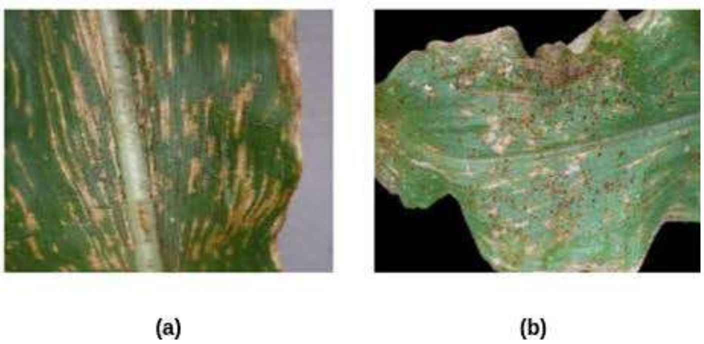

Fig:1 Sample images of each category in the dataset. (a) Gray leaf spot, (b) Common rust.

Fig:2 Sample images of each category in the dataset. (c) Northern leaf blight, and (d) Healthy.

B. DATA PREPROCESSING

The dataset was split into two parts: an 80% training split and a 20% test split for the model's performance evaluation, though the exact split ratio may vary. By taking 20% of the training samples, a validation split was made from the training subset. The model is fed with the training subset in order to make model learn the intricate aspects of the pictures. In contrast, the training subset and the validation subset are maintained apart. In order to monitor the model's performance, subset is feed to model after each epoch to evaluate performance of the model.

C. DATA AUGMENTATION

The dataset has been augmented using a mix of the horizontal flip, shearing, and zooming procedures to prevent over-fitting. The values for each of the augmentation strategies applied are shown in Table 2. Before the subsets were utilized in subsequent processes, photos were finally resized to 224×224 pixels.

Augmentation Technique	Value
Zoom	20%
Shear	20%
Horizontal Flip	False

Table 2. Data augmentation values

IV. DEEP LEARNING MODELS

Adaptive Learning Rate: Adam combines the advantages of the root mean square propagation (RMSProp) and AdaGrad optimizers. Using gradient knowledge from the past, the Adam optimizer adapts the learning rate for each parameter. Adam optimizer's capacity to manage a variety of high-dimensional, big-scale data sets makes it well-suited for training enormous datasets or complicated models which enhances convergence and generalisation.

In our experimental investigation, we mainly used the Adam optimizer in all deep learning algorithms since it automatically adjusts parameters and maintains distinct adaptive learning rates for various parameters, enabling the optimizer to converge more quickly and efficiently explore the parameter space.

InceptionV3 with optimiser adam:

Google created the InceptionV3 convolutional neural network architecture for image categorization problems. The weights and biases of the network are updated throughout the training phase when utilising the InceptionV3 architecture with the Adam optimizer. The neural network's structure and connectivity are determined by the InceptionV3 architecture[26], and its parameters are updated during training using the Adam optimizer. A network is loaded that has utilised the Inceptionv3 of 48-layer deep multilayer architecture, that can often be "pre-trained" using ImageNet [8].and which is pretrained over one million images from the ImageNet database. It is capable of categorising images into more than a thousand distinct categories. In order to efficiently navigate the high-dimensional parameter space and converge to a satisfactory solution, it modifies the learning rate for each parameter separately.

MobileNet:

An effective model for mobile and embedded vision applications is

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provided by MobileNet[27], a simplified architecture that builds lightweight deep convolutional neural networks utilising depthwise separable convolutions. MobileNets are based on a condensed architecture that use depth-wise separable convolutions to construct low weight deep neural networks. We offer two basic global hyperparameters for achieving the best possible latency and accuracy balance.A better module with an inverted residual structure is added in MobileNetV2. This time, non-linearities in thin layers are eliminated. Modern performances are also attained for object detection and semantic segmentation using MobileNetV2 as the foundation for feature extraction.

Densenet121:

One of the image categorization models in the DenseNet collection is densenet-121. All DenseNet models were trained using images from the ImageNet picture database[8]. For example, the first layer is connected to the second, third, fourth, and so on, whereas the second layer is connected to the third, fourth, fifth, and so on. A typical CNN architecture, in which each layer is connected to every other layer, is what the DenseNet architecture is all about.. A layer in DenseNet[13] receives its input from the concatenation of feature maps from earlier levels.

ResNt152v2:

ResNet 152V2: A type of artificial neural network (ANN) is a residual neural network (ResNet). It is a gateless or open-gated variant of the HighwayNet, which had hundreds of layers and was the first operational extremely deep feedforward neural network.

EfficientNetB0:

A convolutional neural network named EfficientNetB0 [7]has been trained on more than a million images from the ImageNet database [8]. The network is able to categorise images into more than a thousand distinct objects, such as keyboards, mouse, pens, and other animals.

CNN:

A CNN is a network architecture for deep learning algorithms that is largely used for applications that analyze pixel input and recognize images. While there are other types of neural networks used in deep learning, CNNs [2] are the preferred network design for object identification and recognization.A deep learning network architecture that directly learns from data is a convolutional neural network (CNN)[15]. Using CNNs, it is possible to identify patterns in images that may be used to identify objects, groups, and categories. CNN [16]is designed to automatically and adaptively learn spatial hierarchies of data via backpropagation and a variety of building blocks, including convolution layers, pooling layers, and fully connected layers.

Xception:

A deep convolutional neural network architecture called Xception (Extreme Inception) is the foundation of depth wise separable convolutions, which seek to keep the expressive power of conventional convolutions while reducing their computing cost. The depth-wise separable convolutional layers with residual connections are stacked linearly in the Xception [9] algorithm. The network can capture both low-level and high-level characteristics at various sizes and levels of complexity because to its stacking structure .By passing parts of the convolutional layers, Xception uses skip connections. These connections minimize the vanishing gradient issue, enhance gradient flow through the network, and help gradient information spread more efficiently during backpropagation.

The depth wise convolution followed by the pointwise convolution is the original depth wise separable convolution.

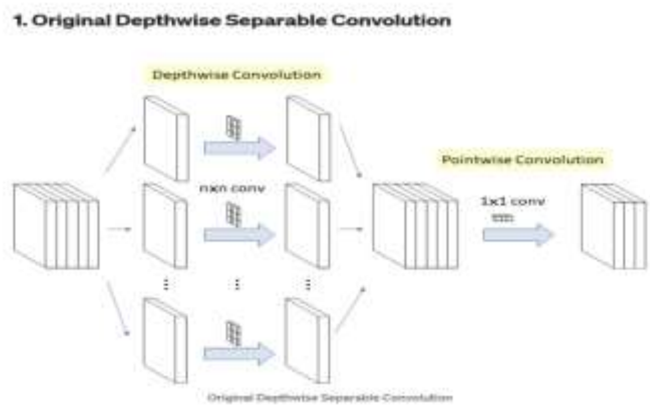

Fig: 3. The channel-wise n×n spatial convolution is depth-wise convolution.

If the figure 2 above had five channels, we would have five n×n spatial convolutions. The 1×1 convolution used to modify the dimension is actually pointwise convolution.

We do not need to conduct convolution across all channels, As a result, there are fewer connections and the model is lighter.

The pointwise convolution is followed by a depthwise convolution to create the modified depthwise separable convolution. The inception module of Inception-v3's 1×1 convolution is performed first before any n×n spatial convolutions, which served as the inspiration for this alteration. As a result, it differs somewhat from the original. (n=3 in this case since Inception-v3 uses 3×3 spatial convolutions.)

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Model	Training		Validation	
	Loss	Accuracy	Loss	Accuracy
InceptionV3	0.1021	0.9605	0.2260	0.9351
MobileNet	0.2390	0.9600	0.8798	0.9233
DenseNet121	0.1760	0.9536	1.8061	0.9221
ResNet152V2	0.4328	0.9066	1.6082	0.8089
EfficientNetB0	0.0037	0.9991	2.6036	0.2127
CNN	0.0171	0.9930	0.1759	0.9320
Xception	0.0182	0.9941	0.1979	0.9592

Table 3:Accuracy of the models used in the experiment.

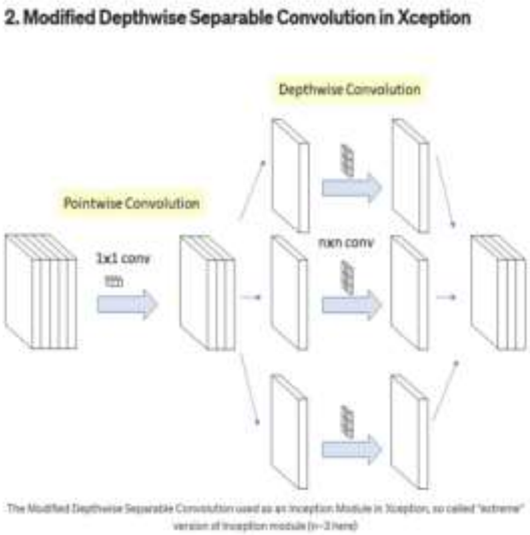

Fig 4. Modified inception module in xception - extreme inception

As previously mentioned, the modified depth wise separable convolution first performs 1×1 convolution, followed by channel-wise spatial convolution, in contrast to the original depth wise separable convolutions, which perform 1×1 convolution first, followed by channel-wise spatial convolution, as they are typically implemented (for example, in TensorFlow).After the initial operation, there is non-linearity in the original Inception Module. There is NO intermediary ReLU non-linearity in Xception, the updated depth wise separable convolution.

V.RESULTS AND DISCUSSIONS

When training is complete, the models are tested against the test subset to determine their effectiveness. The train subset accuracy for the previous models ResNet152, InceptionV3, Efficient-NetB0, and DenseNet121 is 90.66%, 96.05%, 99%, and 95.36%, respectively. In contrast, the test subset accuracy is varied and is displayed in the table. A comparison of the accuracy of the models employed in the experiment is shown in Table 3.

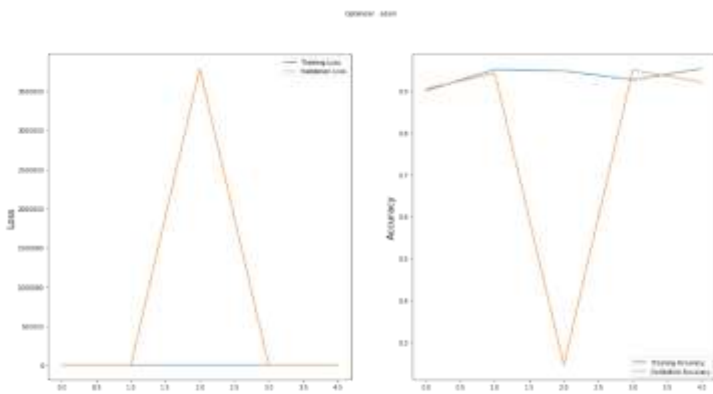

Fig 5. Accuracy & Loss curves of DenseNet121

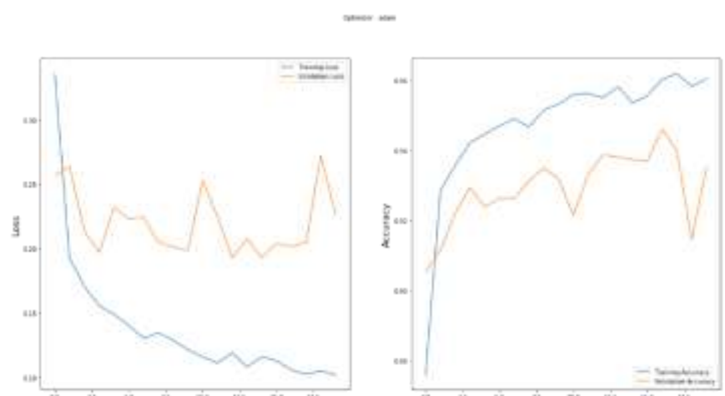

Fig 6. Accuracy & Loss curves of Inception

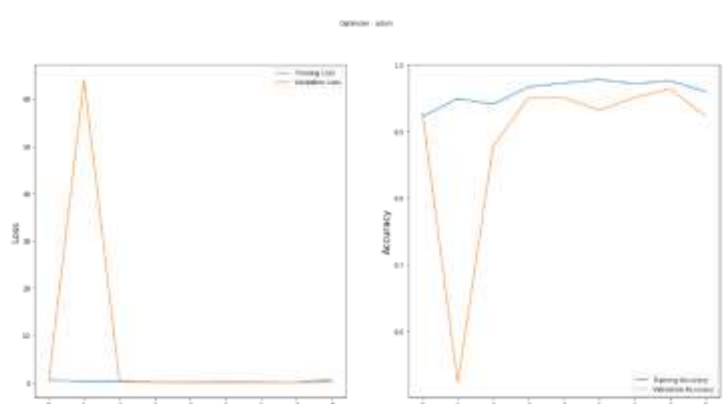

Fig 7. Accuracy & Loss curves of MobileNet

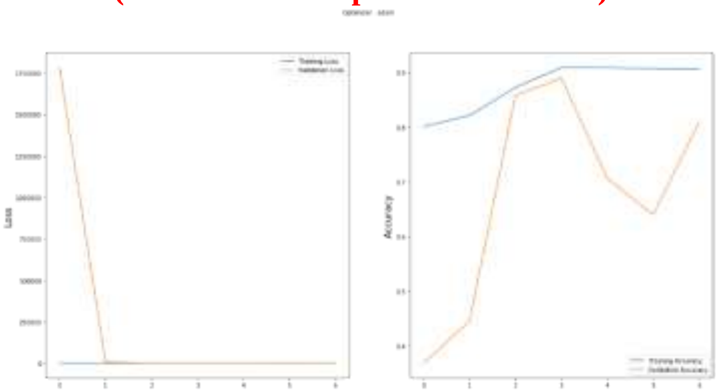

Fig 8. Accuracy & Loss curves of ResNet152V2

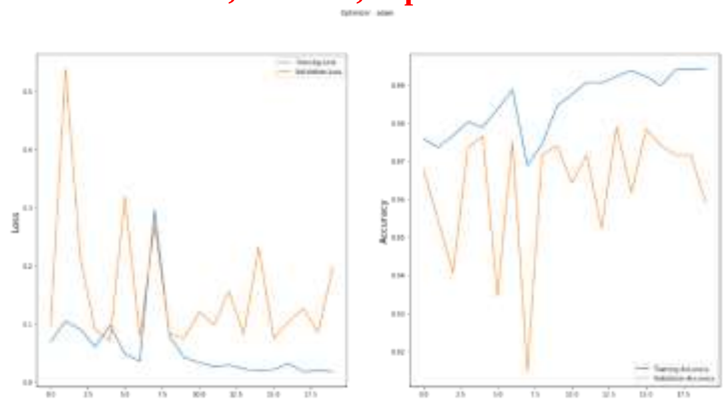

Fig 11. Accuracy & Loss curves of Xception

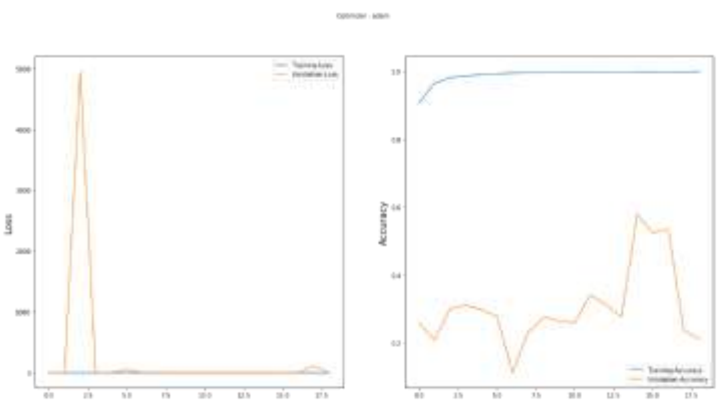

Fig 9. Accuracy & Loss curves of EfficientB0

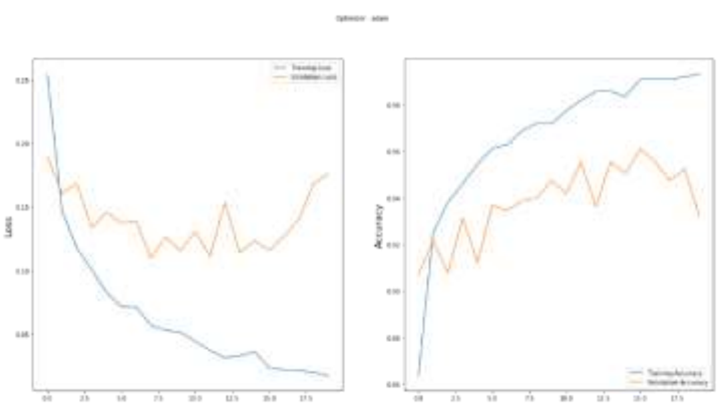

Fig 10. Accuracy & Loss curves of CNN

VI. CONCLUSION

This research study was created with an objective of offering assistance to farmers and agricultural professionals. It may one day be created as a portable programme on an immensely useful handy pocket device . Farmers won't have to travel to a professional's office to ask for advice. The system can be improved by facilitating farmers in identifying levels of disease severity in addition to disease detection. This helps in the early treatment of agricultural and plant diseases.

The technique employed in this paper, which generated a classification accuracy of 99.4%, is evident from the results of the comparison analysis. Additionally, using CNNs with smaller parameters to extract features and combining their feature sets later produces models that are more reliable and outperform CNNs with much larger parameters.

In a follow-up work, we might employ a similar technique to extract other maize pathogens, well as additional illnesses of other plants from digital images. The work of this paper can be extended in various other fields in detection and classification of any other plant or animal diseases with their images. In order to immediately generate new data after learning the properties of illness images, more sophisticated techniques must be used because current data augmentation systems rely heavily on already-existing disease data.

VII. FUTURE SCOPE

- As part of future work, we can use the same method to categorise corn illnesses and other plant diseases using digital photos. Additionally, we can experiment with other augmentation methods and different CNN configurations for feature extraction.

- Additionally, the outcomes of this work can be investigated in other situations utilising various feature extractors and fusion techniques on any dataset. This project can be developed further into an application that can not only identify illnesses but also recommend necessary actions like insecticides, pesticides etc. as well as appropriate climatic conditions, precautions, and methods to farmers in order to protect crops from infections.

- Furthermore, by utilising different feature extractors and fusion methods on any dataset, the results of this study may be examined in a variety of contexts.

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