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DEEP LEARNING-ASSISTED CLASSIFICATION OF CORN LEAF DISEASES

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ABSTRACT:
Maize stands as a vital agricultural crop worldwide, serving as a crucial source of sustenance for humans, livestock feed, biofuel, and a raw material for various products. The detection and management of natural diseases pose a significant challenge for food crops. Swift identification of plant diseases remains a time-consuming and arduous task, particularly for small-scale farmers. Conventional methods and tools lack efficacy, demanding extensive manual labor and time investment. Timely disease detection is imperative for effective treatment and timely implementation of pesticide measures to curb the spread. This research introduces an efficient image classification model based on advanced deep learning techniques, specifically tailored for accurately identifying three prevalent maize leaf diseases. The proposed model employs the Xception model, leveraging transfer learning through pre-trained Xception models for robust feature extraction. The amalgamation of deep features creates a sophisticated feature set, enhancing the model's ability to derive valuable insights from the dataset. With reduced computational costs and the capability to capture essential characteristics, this depth-wise separable Convolutional Neural Network (CNN) exhibits superior efficiency. Comparative analysis against other CNNs, such as EfficientNetB0 and DenseNet121, highlights the exceptional performance of the suggested model, achieving an impressive accuracy of 99.40%. The study underscores the suggested model's superior accuracy and its proficiency in diagnosing various corn leaf diseases.

KEYWORDS: Deep Learning, Corn Leaf Diseases, Image Classification, Convolutional Neural Network (CNN), Xception Model, Disease Detection, Agricultural Automation, Precision Farming, Crop Disease Management, Plant Pathology.

1. INTRODCUTION:

Corn (Zea mays), a widely cultivated staple crop, plays a crucial role in global food security and various industries, including livestock feed, biofuel production, and manufacturing. However, the threat of corn leaf diseases poses a significant challenge to crop productivity and sustainability. Early and accurate identification of these diseases is critical for implementing timely and effective management strategies [1].

Traditional methods of disease detection often require extensive manual labor and time, limiting their practicality, especially for small-scale farmers. In recent years, advancements in deep learning techniques have shown remarkable promise in automating and enhancing disease identification processes in agriculture [2].

CNNs especially and other deep learning models are becoming increasingly popular for their ability to facilitate accurate disease categorization in plant images. This research makes use of these tools to create a deep learning-assisted categorization system for easy, quick detection of widespread corn leaf diseases. [3].

By utilizing a sophisticated neural network architecture and advanced image processing techniques, this research aims to offer a comprehensive solution for accurate and efficient disease management in corn cultivation [4].

With the global population projected to reach 9.7 billion in the near future, ensuring sufficient food production presents a substantial challenge. The rapid expansion of the population and the subsequent rise in food demand necessitate increased crop yields. Plant diseases have a detrimental impact on overall crop yield, exacerbating food scarcity [5].

It is thought that plant diseases cost the worldwide agriculture industry over $60 billion annually in lost crop value. Plant diseases are a major concern for the world's food supply, highlighting the importance of maintaining high standards for agricultural production. Currently, maize stands as the leading food crop globally, serving as a vital food source and a fundamental raw material for various industries [6].

Corn production plays a crucial role in ensuring food security, enhancing farmer incomes, and contributing to the nation's economic well-being [7].

The productivity and quality of corn are directly affected by diseases, with more than a dozen prevalent diseases afflicting maize, primarily targeting the leaves, ears, and roots of the plant [8].

Leaf damage is particularly common among these diseases. This study focuses on three specific corn leaf diseases, namely:

Northern Leaf Blight: Exserohilum turcicum, a fungal pathogen, is responsible for Northern Leaf Blight. This disease is characterized by cigar-shaped lesions on the leaves, potentially leading to leaf blight. Severe infections can significantly reduce both yield and crop quality [9]**.**

Gray Leaf Spot: The fungus Cercospora zeae-maydis is responsible for gray leaf spot. It is identifiable by small, rectangular lesions on the leaves, varying in color from grey to tan. If left unattended, these gray leaf spots have the potential to decrease crop yield [10]**.**

Common Rust: Common Rust, also known as the fungus Puccinia sorghi is responsible for maize rust. Its symptoms include small, round to elongated pustules on the leaves and husks of maize plants. These pustules, filled with spores, typically exhibit an orange to reddish-brown coloration [11].

Early identification of these leaf diseases is crucial for effectively managing and preventing their impact on maize plants. However, traditional methods for identifying these diseases in agricultural fields require visual inspections conducted by experts, followed by laboratory diagnosis [12].

This approach is associated with the following drawbacks:

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

The limitations of the traditional approach, intelligent diagnosis of these diseases can be achieved through the utilization of deep learning technology in conjunction with image processing [13].

As the capacity of computers to analyze data grows, it becomes possible to create automated & intelligent applications for identifying plant diseases through the use of AI, ML, and DL [14].

This study introduces novel approaches for categorizing digital images of maize leaves based on the presence of common rust, northern leaf blight, and grey leaf spot. [15].

To consolidate predictive capabilities and formulate a robust classification model, the study uses optimum parameter ranges for pre-trained convolutional neural networks (CNNs) include the EfficientNetB0, DenseNet121, Mobile Net, as well as Xception simulations. [16].

The study conducts a comparative analysis of their accuracies and performances, suggesting the most suitable model [17].

The following concise statement summarizes the primary objectives of our research:

- Achieve more accurate classification with a manageable number of parameters.
- Develop a model for the recognition and detection of illnesses in maize plants through comprehensive testing and evaluation of the proposed model in comparison to other models [18].

2. LITERATURE SURVEY:

To aid in the diagnosis of plant diseases, researchers have created a novel technique for identifying photos of leaves using deep convolutional networks. Thanks to the model's ability to account for contextual cues, 13 different types of plant diseases may be distinguished from healthy leaves [19].

In order to train the deep CNN, the deep learning framework Caffe was used. The accuracy of the built model, as measured by experiment, ranged from 91% to 98% for separate class tests [20].

There are a total of nine layers in the CNN, featuring three convolutional, three max-pooling, and two fully connected layers. On a subset of the Plan Village dataset including maize leaves affected with corn grey leaf spot, corn common rust, and corn northern leaf blight, as well as a healthy class, the model achieved 94% classification accuracy [21].

Utilizing the Plan Village dataset, the authors propose the use of a dense-optimized Convolutional Neural Network (CNN) to classify the four distinct types of maize leaves. The architecture of the network comprised five dense blocks, culminating in the addition of a SoftMax classifier layer. As a result of the training, the CNN attained an impressive classification accuracy of 98.06 percent across the four classes employed in the experimental analysis [22].

According to their research, numerous plant infections, each with only a few hundred nucleotides in common with higher plants, are responsible for many of the diseases that plague our crops. Their effects could range from merely annoying to catastrophic, wiping out entire food-crop-growing regions [22]. Devastating plant disease has contributed to the global food scarcity that has left at least 800 million people hungry. The complex genotypic distributions of plant disease populations make eradication difficult. It is important to realize that plant diseases threaten our food supply.[23].

In order to merge contextual and visual information, the authors of presented a multi-context fusion network. Factors in the plant's surroundings (such temperature and humidity) that can cause or exacerbate specific diseases were also considered [24].

Classifying these factors helped the network throughout the identification stage and led to a 97.50% accuracy in classification.

The authors proposed a CNN-based approach for the identification of maize leaf diseases. To enhance the precision of the CNN model, they augmented the training set with additional data and employed transfer learning techniques [25].

Across four specific types of maize leaves (corn grey leaf spot, corn common rust, corn northern leaf blight, and healthy leaves), the optimized CNN demonstrated an average accuracy of 97.6% on a subset of the Plant Village dataset. In Utilizing computer vision techniques makes it possible to automate this process, which is crucial for agricultural applications [26].

In this study, the effectiveness of three cutting-edge convolutional neural network architectures for categorizing maize leaf diseases is evaluated. They have used improvement techniques including data augmentation, Bayesian hyperparameter optimization, and fine-tuning tactics [27].

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 [28].

According to the findings, 97% of the CNN models tested were accurate in classifying maize leaf disease.

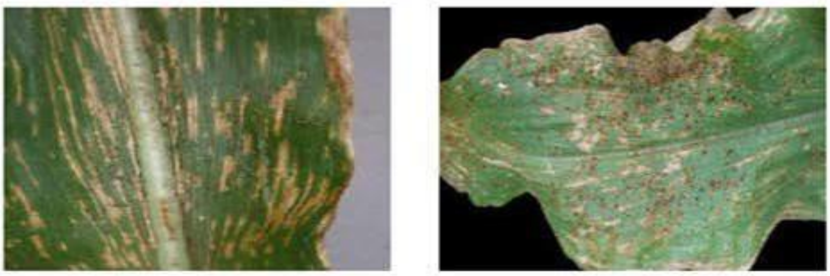
A revolutionary new database called "ImageNet" has been released; it is a large ontology of images built on top of the WordNet architecture. WordNet's 80,000 synesis will be largely populated by 500-1000 high-quality images sourced from ImageNet. Their research provides a thorough examination of ImageNet in its present configuration, which consists of 12 subtrees, 5247 synsets, and 3.2 million total pictures and then sample image of each category of dataset is shown in Fig 2. 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.

3. METHODOLOGY:

Dataset Description: The experiment utilized a dataset comprising numerous comprehensive photographs of maize leaves, captured at different growth stages and in diverse environmental conditions. The dataset includes a total of 13,345 photos, categorized into healthy and diseased maize leaves. The dataset encompasses images of corn leaves afflicted by four distinct diseases, namely, common rust, grey leaf spot, and northern leaf blight. Figure 1 displays representative images from each category included in the dataset, while Table 1 offers a comprehensive breakdown, presenting the number of photographs available within each category. The primary objective of this dataset is to streamline the process of constructing and evaluating deep learning models tailored for tasks associated with the classification of maize leaves.

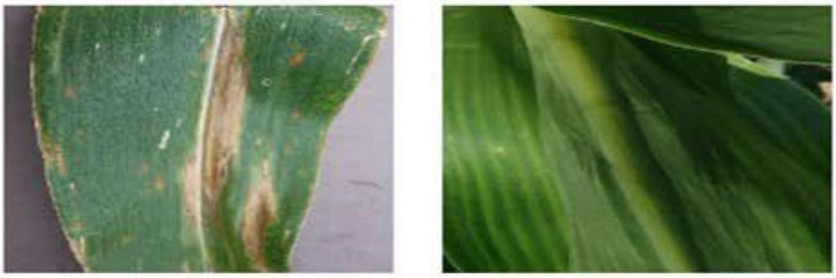
Table 1. Each dataset category's image count.

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



(a) (b)

Figure:1 Sample images representing each category in the dataset are as follows: (a) Gray leaf spot, and (b) Common rust**.**



(c) (d)

Figure:2 Sample images depicting each category in the dataset are as follows: (c) Northern leaf blight, and (d) Healthy.

Data Preprocessing: The database has two sections, consisting of an 80% training split and a 20% test split, although the specific ratio of the split may vary In addition, a validation subset was generated by dividing the training data (of which 20% were used). This method guaranteed that the model was given an adequate training subset to understand the nuanced details of the photos. It's important to note that we maintained the validation data apart from the training data. To continually monitor the model's performance, the subset was fed to the model after each epoch, enabling the evaluation of the model's performance over time.

Data Augmentation: To prevent overfitting, the dataset underwent augmentation, using a method that combines horizontal flipping, shearing, and zooming. The values used for each enhancement method are shown in Table 2. In the end, the pictures were scaled down to 224 x 224 pixels before being used in the subgroups in future processes.

Table 2. Data augmentation values

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

Deep Learning Models: The Adaptive Learning Rate: Adam optimizer combines the strengths of the RMSProp and AdaGrad optimizers. By leveraging historical gradient information, the Adam optimizer dynamically adjusts the learning rate for each parameter. Its adaptability in handling high-dimensional, large-scale datasets makes it particularly suitable for training extensive datasets and complex models, facilitating improved convergence and generalization. Throughout our experimental investigation, the Adam optimizer was predominantly employed in all deep learning algorithms. Its inherent capability to automatically adapt parameters and manage distinct adaptive learning rates for various parameters allowed the optimizer to achieve quicker convergence and efficient exploration of the parameter space.

InceptionV3 with optimizer Adam: Google created the InceptionV3 convolutional neural network architecture for image categorization problems. During training, the network's weights & biases are continuously adjusted. when utilising the InceptionV3 architecture with the Adam optimizer. The neural network's structure and connectivity are determined by the InceptionV3 architecture, and its parameters are updated during training using the Adam optimizer. A network is loaded that has utilized the Inceptionv3 of 48-layer deep multilayer architecture, that can often be "pre-trained" using ImageNet 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: MobileNet is a smart architecture that creates light deep convolutional neural networks using depth wise separable convolutions. It works well for mobile and embedded vision apps. You can build low-weight deep neural networks with mobileNets by using depth-wise separable convolutions and a condensed design. Because we want to get the best mix of latency and accuracy, we offer two basics global hyperparameters. MobileNetV2 has updated a better module that has a reversed residual structure. Unevenness in thin layers is taken care of this time. Using MobileNetV2 as the base for feature extraction also leads to modern solutions for finding objects and separating them into conceptual groups.

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. For example, one can connect the first layer to the second, third, etc., and the second layer to the third, fourth, etc. The DenseNet design is representative of the standard form of Convolutional Neural Networks (CNNs) in which all layers are interconnected. In DenseNet, the feature maps from lower layers are combined and sent into higher layers as input.

ResNt152v2: ResNet 152V2: A type of artificial neural network (ANN) is a (ResNet) residual network in neural networks. HighwayNet, the first fully functional extremely a hundreds-of-layers-deep feedforward neural network. The gates in this model are open, making this a type of HighwayNet.

EfficientNetB0: With over a million photos from the ImageNet database, a convolutional neural network called EfficientNetB0 has been trained. More than a thousand different things, including keyboards, mice, pens, and other creatures, may be identified by the network in one image.

CNN: CNNs are a popular network design for deep learning algorithms used in image recognition and analysis applications. For object recognition and identification, CNNs are the most popular deep learning neural network architecture. Convolutional neural networks (CNNs) are a type of deep learning network design that acquires knowledge directly from data. The use of CNNs allows for the detection of picture patterns that may be applied to the classification and labeling of various graphical entities. Convolutional Neural Networks are constructed with convolution layers, pooling layers, fully connected layers, & backpropagation to discover spatial hierarchy in input data automatically and adaptively.

Xception: The fundamental basis for depth-wise separable convolutions is a sophisticated convolutional neural network structure known as Xception (short for Extreme Inception), 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 algorithm. The stacking structure of the network enables the capturing of both low-level and high-level properties across different sizes & levels of complexity. By selectively bypassing certain components 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.

One of the first depth-separable convolutions was the depth-wise one, which was then followed by a point-wise one.

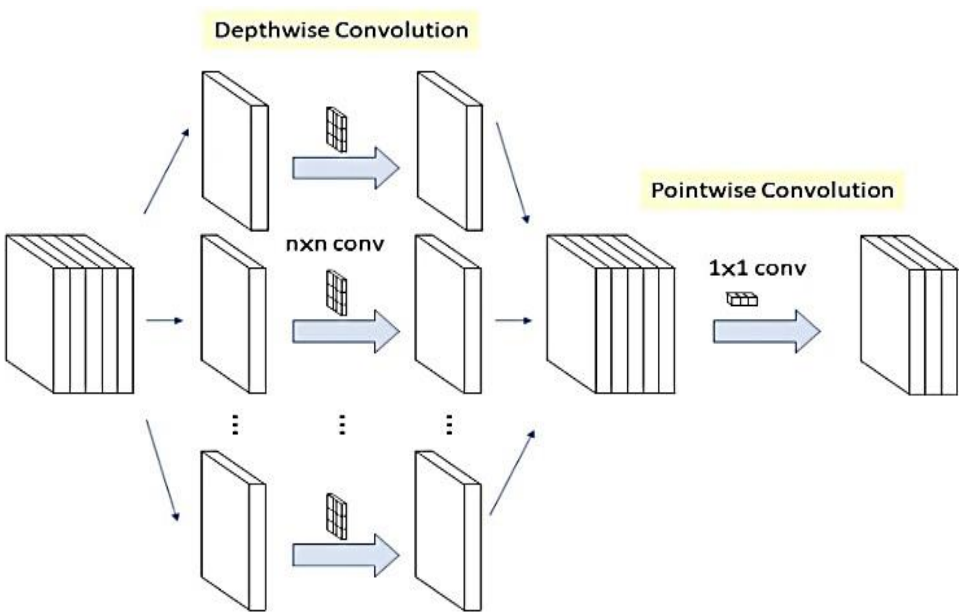


Fig: 3. Depth-wise convolution characterizes the channel-wise nxn spatial convolution.

The nxn spatial convolutions in Figure 3 would increase to 5 if there were 5 channels. Pointwise convolution is employed in the 11 convolution that is used to alter the dimension. Since we don't have to perform channel-wide convolution, the model can function with fewer nodes and fewer connections.

The improved depth wise separable convolution is obtained by doing the pointwise convolution followed by the depth wise convolution. The rationale behind this alteration stems from the observation that the initial execution of the inception module in Inception-v3 involves the 11 convolutions, which takes place prior to any spatial convolutions in the neural network. This causes some modifications from the source material. Since Inception-v3 employs 33 spatial convolutions, we can assume that n is equal to 3. Figure 4 is an example of the updated inception module in xception's extreme inception.

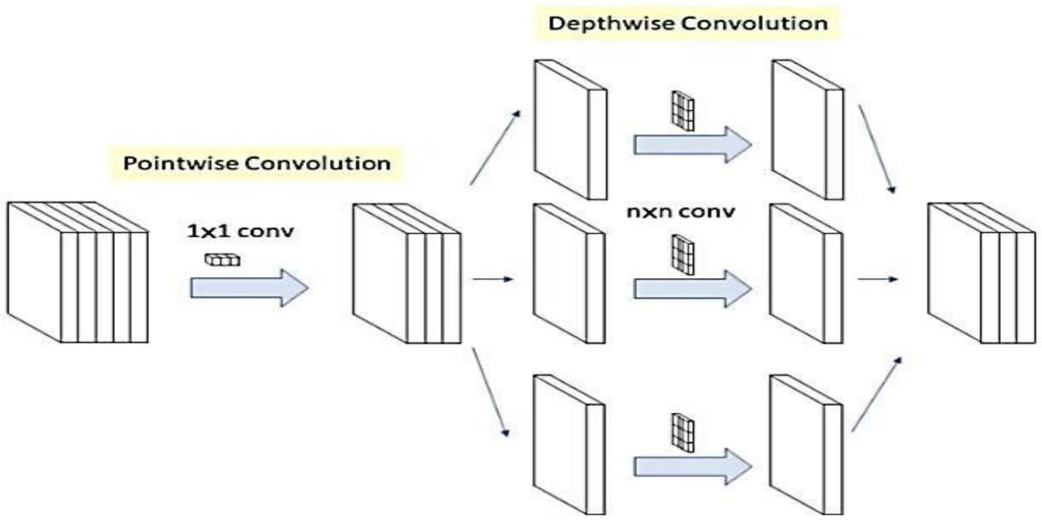


Fig 4. Modified inception module in xception - extreme inception

While conventional implementations of depth-wise separable convolutions (such as TensorFlow) execute 11 convolutions first, the modified depth-wise separable convolution conducts 11 convolutions before moving on to channel-wise spatial convolution. After the initial operation, the original Inception Module exhibits non-linear behavior. Unlike its predecessor, the depth-wise separable convolution Xception does not introduce any non-linearity via an intermediate ReLU.

4. RESULTS:

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. Table 3 displays a comparison of the experimental models' accuracies.

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

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

The below figures show the accuracy & Loss curves of the DenseNet121 of the graph is shown in Fig 5. and then the Accuracy & Loss curves of the Inception is shown in Fig 6 and in the Fig 7 shows the Mobilenet graph and the graph Accuracy And loss curves of the ResNet152v2 is shown in the Fig 8 and the Fig 9 displays the EfficientB0 of the graph and then the fig 10 And the Fig 11 shoes the curves of CNN & Xception.

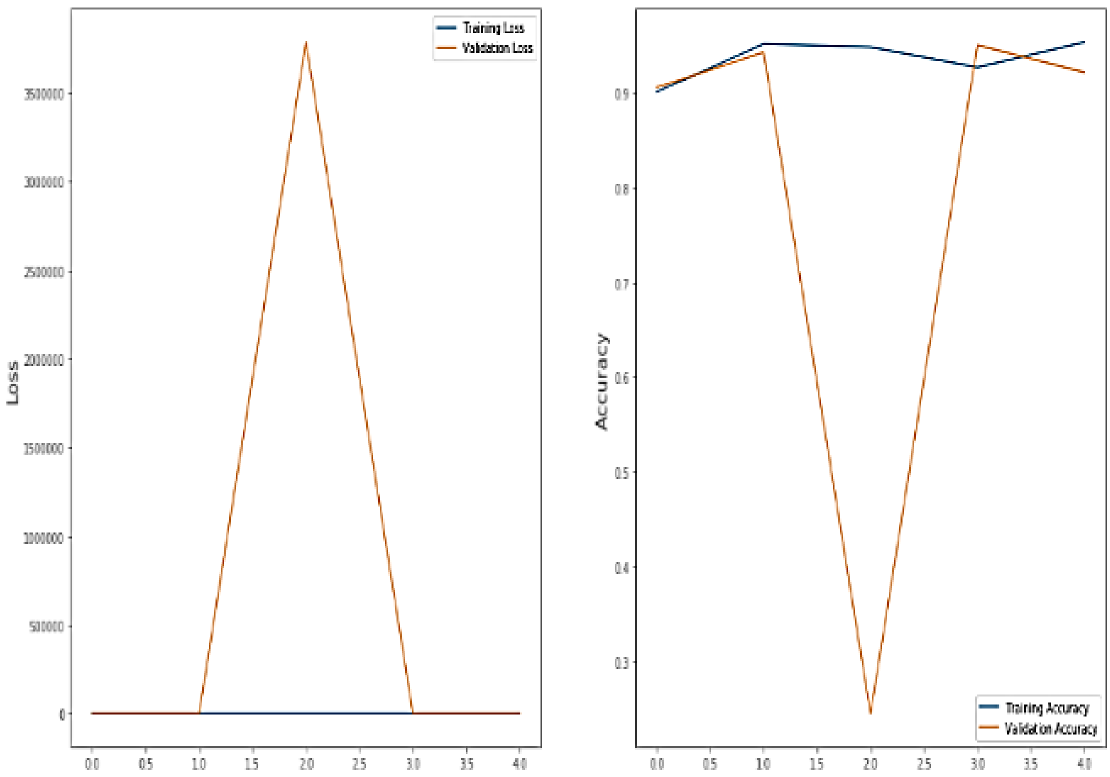


Figure 5. Accuracy & Loss curves of DenseNet121

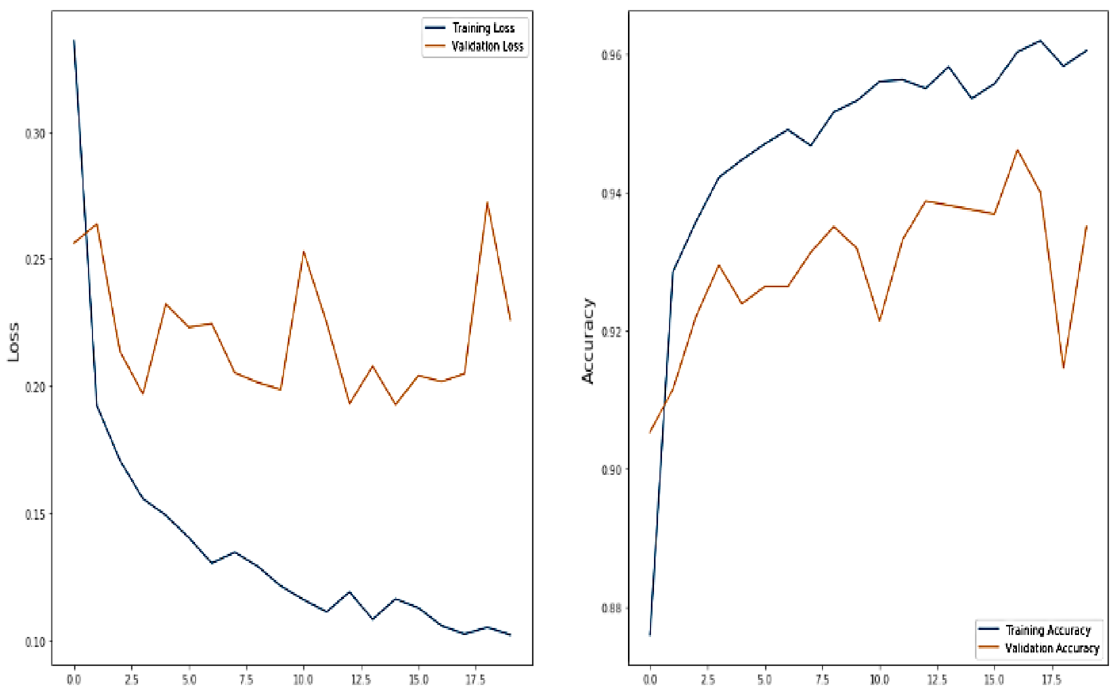


Figure 6. Accuracy & Loss curves of Inception

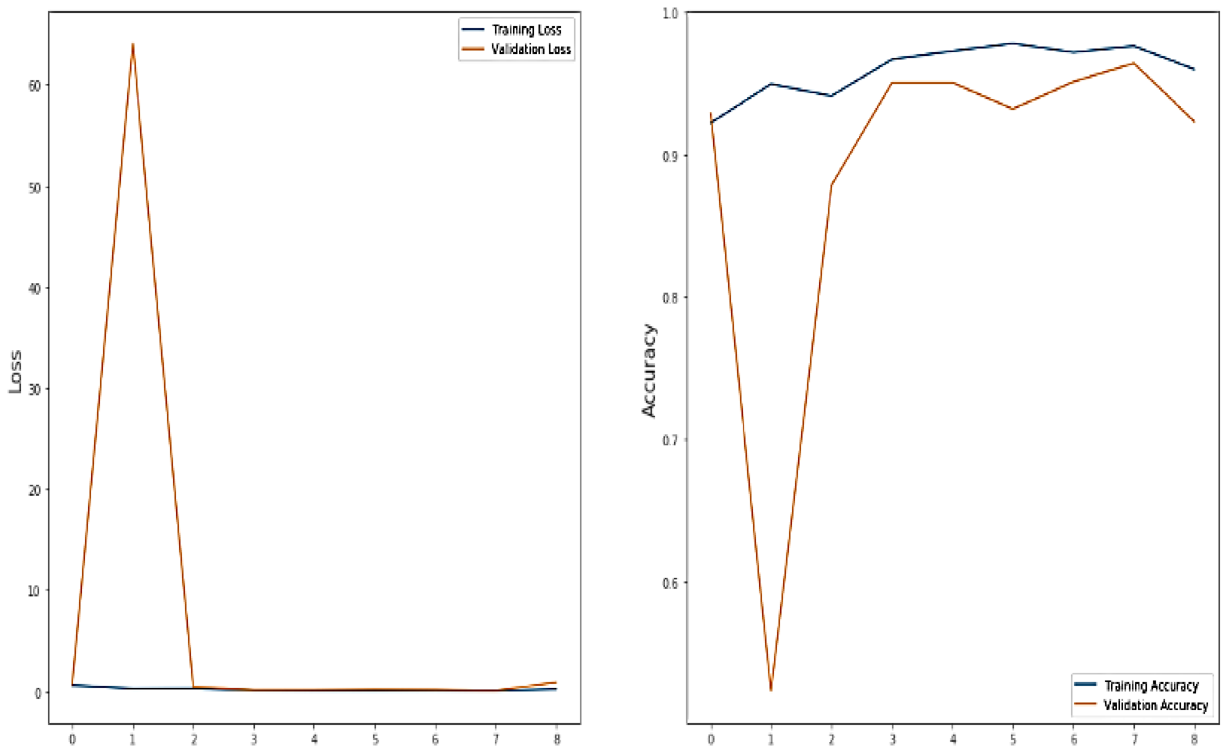


Figure 7. Accuracy & Loss curves of MobileNet

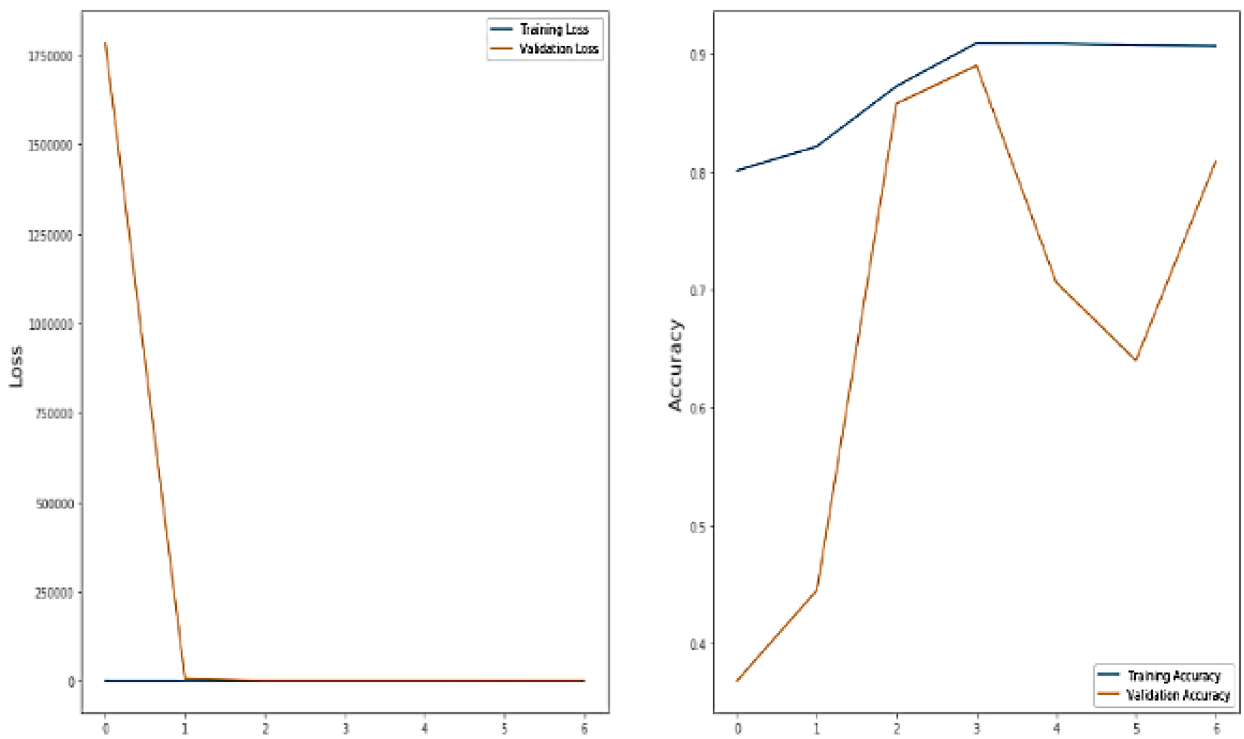


Figure 8. Accuracy & Loss curves of ResNet152V2

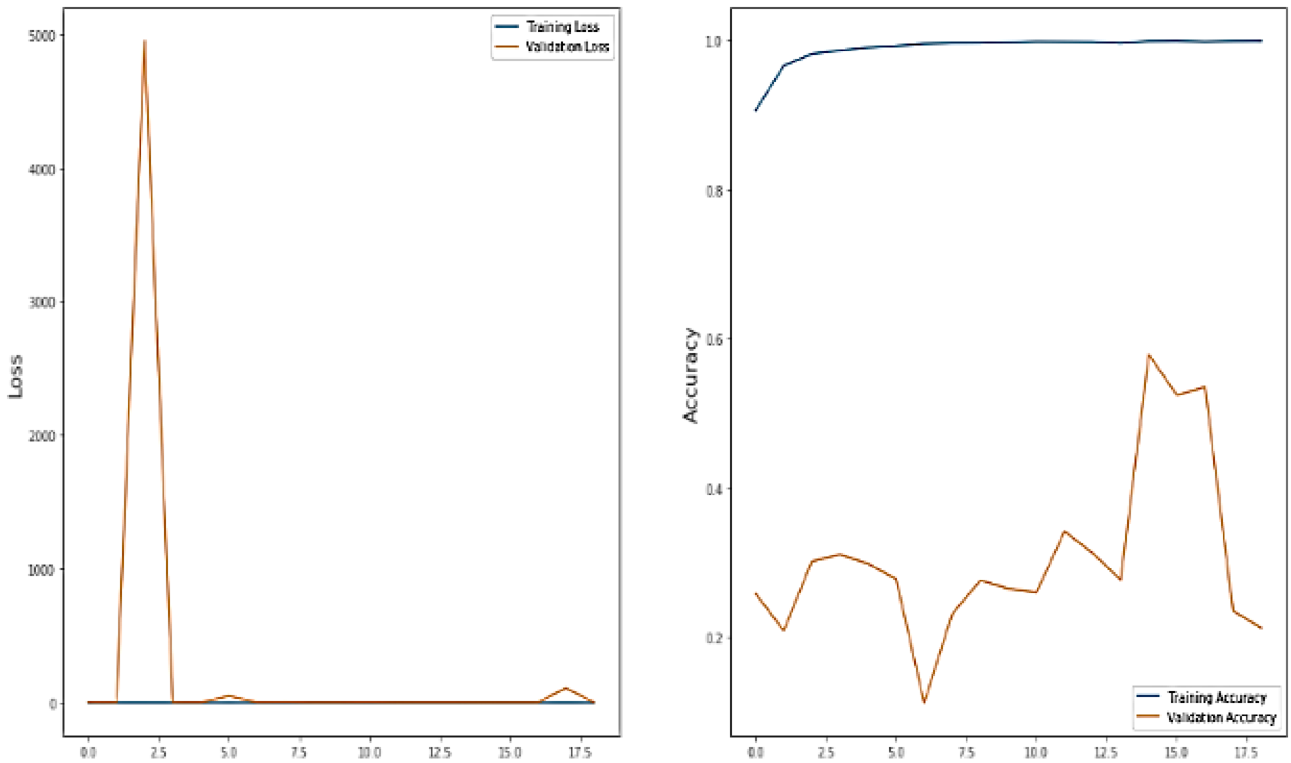


Figure 9. Accuracy & Loss curves of EfficientB0

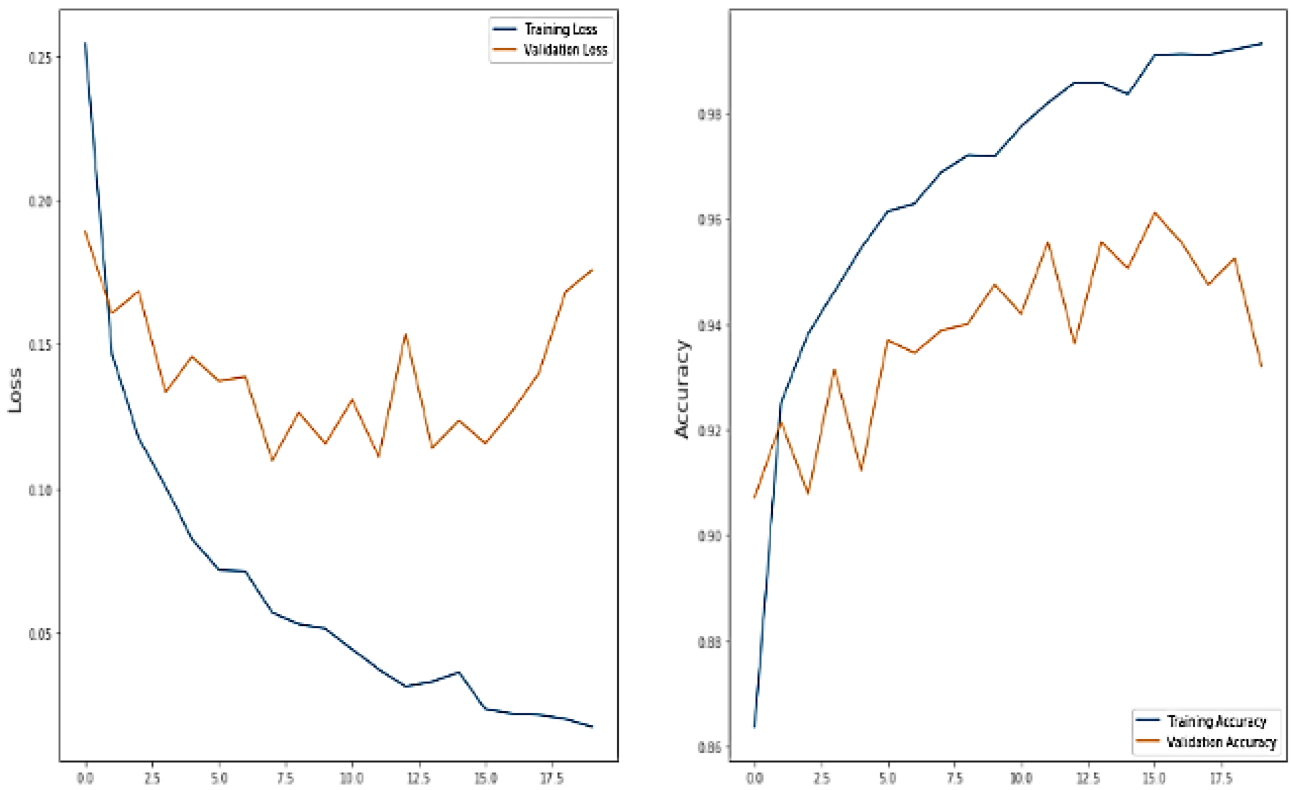


Figure 10. Accuracy & Loss curves of CNN

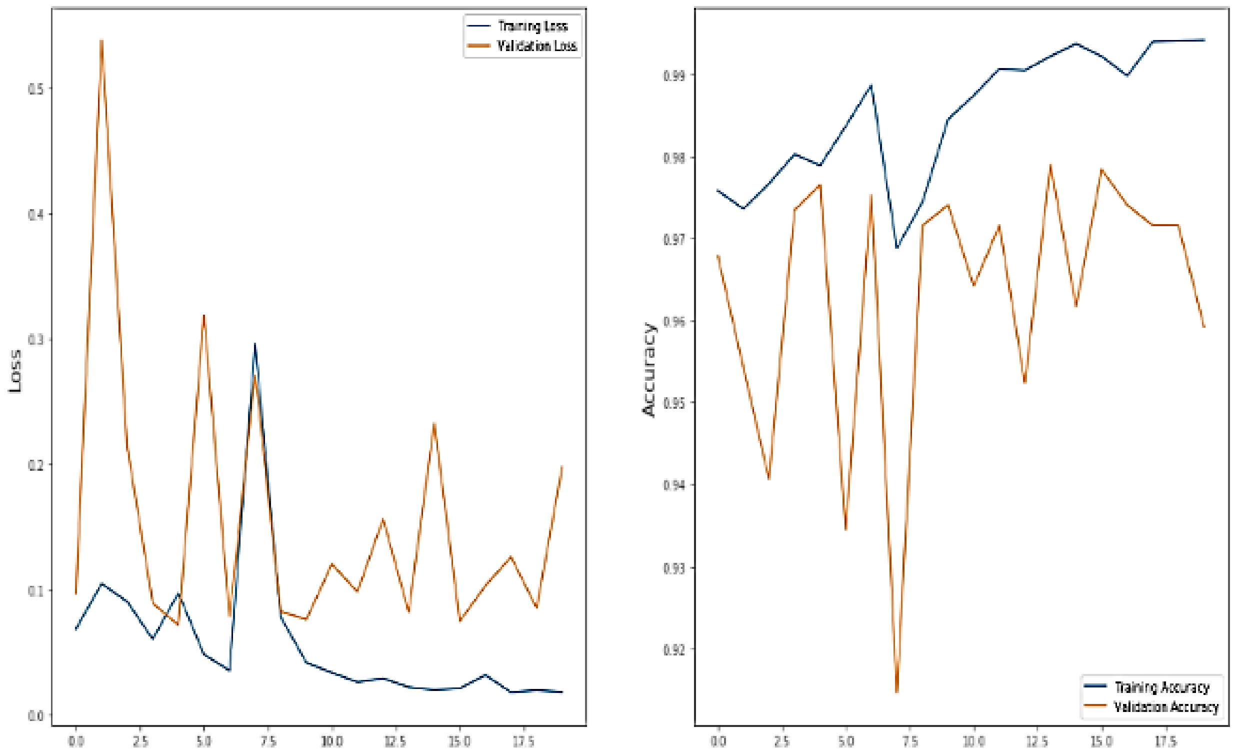


Figure 11. Accuracy & Loss curves of Xception

5. CONCLUSION:

This research study was undertaken to provide assistance to farmers and agricultural professionals. The ultimate goal is to develop a portable program that can be accessed through a convenient handheld device. This innovation would alleviate the need for farmers to make trips to seek advice from professionals. The technology can be improved such that it not only detects diseases but also helps farmers determine their severity. This early detection capability is crucial for prompt and effective treatment of agricultural and plant diseases. The methodology employed in this study, which yielded an impressive classification accuracy of 99.4%, is evident from the results of the comparative analysis. In addition, smaller parameter Convolutional Neural Networks (CNNs) are being used for feature extraction combining their feature sets, has led to the development of more reliable models whose parameters are orders of magnitude bigger than those used by CNNs. In future endeavors, we plan to employ a similar technique to identify other maize pathogens, as well as various ailments affecting other plant species, based on digital images. The findings of this paper can be extrapolated to various other domains, enabling the use of computer vision techniques to identify and categorize diseases in living organisms. However, to ensure the immediate generation of new data post the acquisition of insights from the disease images, more sophisticated techniques are necessary, as the current data augmentation systems heavily rely on pre-existing disease data.

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