A Lightweight, Computation-Efficient CNN Framework for an Optimization-Driven Detection of Maize Crop Disease

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Abstract: Detecting and mitigating crop diseases can prevent significant yield losses and economic damage. However, most state-of-the-art solutions can be expensive computation-wise. This paper presents an efficient Lightweight multi-layer convolutional neural network (ML-CNN) to identify maize crop diseases. The proposed model aims to improve disease identification accuracy and reduce computational costs. The model was optimized by adjusting parameters, setting convolutional layers, changing the combinations of the pooling layer, and adding dropout layers. By optimizing the model architecture, we create a software tool that can be deployed in resource-limited environments, an ideal choice for deployment on embedded platforms. The PlantVillage dataset was used to train and test the model implementation, including images of healthy and two disease-affected leaves. The performance of the proposed model was compared with pre-trained models such as InceptionV3, VGG16, VGG19, and ResNet50. The analysis results show that the proposed model improved identification accuracy by 16.32%, 1.48%, 1.28%, and 2.26%, respectively. Additionally, the proposed model achieved identification accuracy of 99.60% on the training data and 98.16% on the testing data and also reduced iteration convergences and computational costs.

1 INTRODUCTION

Most farmers in the farming industry have small to medium land for crops. Therefore, they rely heavily on the quality of crop yield (FAO, 2020). However, regional environmental conditions, crop diseases and other factors influence crop yield (Zimmermann et al., 2017). Due to a lack of resources, small-to-medium farmers cannot use high-quality fertilizers to increase crop yield. Farmers frequently use non-technological methods to detect disease, making it challenging to assess its severity (Al Bashish et al., 2010). As a result, a solution that can provide a farmer with authentic, accurate, and timely agro advice at a low cost is of capital interest. A farmer typically seeks agronomic advice on disease or pests by calling an expert and describing visible symptoms. Maize is a member of the Gramineae family, which ranks third in terms of overall yield and cultivated area after wheat and rice (Kaur et al., 2020); with a productivity of 5.82t/ha, the growing global yield was approximately 1.17 billion MT in 2020 (FAO, 2020).

The literature has extensively utilized deep learning (DL), or machine learning, as a successful means of identifying plant diseases (Mohanty et al., 2016; Olawuyi and Viriri, 2022; Divyanth et al., 2023; Tirkey et al., 2023; Jasrotia et al., 2023; Chauhan et al., 2022; Haque et al., 2023; Karlekar and Seal, 2020; Vallabhajosyula et al., 2022; Ji et al., 2020; Manzoor et al., 2023).

However, due to data disparities, identifying an efficient DL architecture with optimal parameters and classification functions is always a difficult task (Tirkey et al., 2023; Uchida et al., 2016). Moreover, most of the proposed studies in the literature, to provide accurate estimation and classification of the crop health state, rely on the processing of massive data (graphical images) using deep neural networks and machine learning models (Yang et al., 2023; Esgario et al., 2020; Demilie, 2024) to achieve high accuracy,

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making the computation cost one of the barriers to adopt and deploy such solutions on resource-limited computation systems such as embedded platforms (Barbedo, 2016; Demilie, 2024; Jensen et al., 2023) and consumer devices such mobile phones (Waheed et al., 2023).

This paper proposes multi-layer convolutional neural networks (ML-CNN) to identify maize crop diseases. The proposed ML-CNN is designed to have fewer parameters, less memory usage, and lower computational cost than existing models while maintaining high accuracy. Our model is designed to learn relevant features directly from the input images without relying on pre-trained architectures. By optimizing the model architecture, we designed and implemented a software tool to identify and classify maize crop state of health, deployable in resource-limited environments.

The main contributions of this paper are as follows:

- An efficient multilayer convolutional neural network-based model is proposed to identify maize crop disease. This model can accurately identify maize crop diseases and reduce iteration convergences in a complex environment.
- The proposed model achieves a high identification accuracy compared to pre-trained CNN models and architectures.
- The number of parameters in the proposed model is optimal compared to state-of-the-art models.
- The implementation of the proposed ML-CNN significantly reduces the computational and memory resources required for crop disease identification, making it practical for use in real-world embedded systems.
- Thorough experimental analysis and comparison to the state of the art for validation.

The rest of the paper is structured as follows: Section 2 is a backrgound. Section 3 cites relevant related work. Section 4 depicts the architecture and modules of the proposed ML-CNN model. Section 5 describes the dataset and processing methods we utilized in this paper. Section 6 discusses the results and comparison, whereas Section 7 concludes the paper.

2 BACKGROUND

Convolutional neural network (CNN) (Saleem et al., 2022) is a powerful deep learning model for computer vision applications including image classification, object detection, and recognition. In general, the main layers of CNN are convolutional, pooling, ReLu, and fully connected layers. Some variants of CNN, such as InceptionV3, VGG19, VGG16, and ResNet50, are given below, along with the proposed model for disease identification in maize crops.

InceptionV3 Model. Inception models are the types of CNN designed mainly for image classification. Google develops these models through different versions (V1, V2, V3), where each model optimizes on the previous architecture. It comprises inception blocks, and InceptionV3 is a pre-trained 48-layer model trained on millions of ImageNet dataset images with a 224x224 input size. The model extracts general features and classifies images with new fully connected layers of 256 and 128 units size and the softmax activation function in the output with three classes for classification.

VGG-16 Model. VGG16 is a 16-layer pre-trained CNN-based model used for image classification. There are 13 convolutional layers and three fully connected layers. It features a unique architecture with a small 3x3 filter size and stride of 1 in the convolutional layers and a 2x2 max-pooling layer with stride 2. The model uses 64, 128, 256, and 512 filters in the first to fifth convolutional layers, followed by three fully Connected (FC) layers with 4096 neurons each. This model represents a baseline for our paper, where the first two FC layers are to contain 256 and 128 units of neurons. In contrast, the output layer has a softmax activation function for classifying into a specified number of classes.

VGG-19 Model. VGG19 model is a 19-layer variation of the VGG model, including 16 convolutional layers, 5 Maxpooling layers, 3 FC layers, and an output layer. The model uses a ReLu activation function and a 3x3 kernel with a 1-pixel stride to classify images effectively. The first two layers comprise 64 filters with a 3x3 kernel and stride 1. Max-pooling layers with a 2x2 window size and stride two are used to reduce the image dimensions. Additional convolution layers with 128 and 256 filters are used, with a final FC layer flattening the volume to 7x7x512 and using 256 and 128 neurons with an activation function softmax in the final layer.

ResNet50 Model. ResNet50 is a 50-layer CNN model designed to resolve the vanishing gradient problem in deep networks through skip connections. The ResNet50 architecture uses a bottleneck building block and a stack of three layers, making it computationally more efficient. The model takes a 224x224 image as input, and was successfully used on a maize crop dataset to classify diseased and healthy leaves.

3 RELATED WORK

Classification remains the primary focus of DL-based plant disease identification in its early stages. Olawuyi et al. (Olawuyi and Viriri, 2022) used deep learning and CNNs for detecting and classifying crop (corn and potato) diseases using a pre-trained resnet50 model. The authors' model achieved an accuracy of 98.0%. In a similar way, Divyanth et al. (Divyanth et al., 2023) presented a two-stage deep learning approach that can precisely identify and estimate the severity of three corn diseases using a custom dataset. The proposed approach uses CNNs for identification and preprocessing techniques such as CLAHE and RGB to HSV conversion. The model achieves an accuracy of 96.76% on the plant village maize crop dataset.

Chauhan et al. (Chauhan et al., 2022) highlighted the challenges of detecting crop diseases in India, especially for smallholder farmers. They developed a low-cost solution utilizing feature extraction using RegNet, dimensionality reduction using Kernel-PCA, and XGBoost classification. Results indicate an accuracy of 96.74%, demonstrating intelligent systems' potential to benefit smallholder farmers. Yang et al. (Yang et al., 2023) proposed a solution, Maize-YOLO, to detect maize pests in real time with high precision. The solution utilizes YOLOv7 as a backbone network and improves accuracy and detection speed by integrating CSPResNeXt-50 and VoVGSCSP modules. When evaluated on a comprehensive pest dataset, Maize-YOLO achieved 76.3% mean average precision (mAP) and 77.3% recall. Using the same dataset with 15200 images, the authors of (Kumar et al., 2020) utilized ResNet34 to detect plant leaf diseases and achieved 99.40% accuracy.

Gayathri et al. (Gayathri et al., 2020) used transfer learning to classify tea leaf diseases using the pre-trained model LeNet, resulting in an accuracy of 90.23%. Using ResNet50, the authors suggested an effective method for identifying and estimating the degree of biotic agent-induced stress in coffee leaves from the PlantVillage database. The proposed method accurately estimated biotic stress at 95.24% and severity at 86.51% (Esgario et al., 2020).

Huang et al. (Huang et al., 2023) proposed a fully convolutional switchable normalization dual path networks model to identify and detect tomato leaf diseases. The model combines an FCN algorithm based on the VGG-16 model to segment the target crop images and an enhanced DPN model to extract the features of the crop. Resnet and DesNet layers are combined and adaptive parameters are optimized to optimize the network's versatility for different diseases and speed of training, achieving thus an accuracy of 97.59%.

The article (Arun and Umamaheswari, 2023) presents a novel approach to identify and categorize plant leaf diseases. The proposed method utilizes an advanced mobile network-based CNN (OMNCNN) that optimizes detection by incorporating several key stages, including preprocessing, segmentation, feature extraction and classification. The experimental results demonstrate that the OMNCNN model surpasses the current state-of-the-art techniques, achieving a precision rate of 0.985, a recall rate of 0.9892, an accuracy rate of 0.987.

The authors of (Ramcharan et al., 2019) developed a transfer-learning solution to identify three diseases and two pests damaging cassava plants, deployable on resource-constrained environments such as smart phones. Although the solution is computation-efficient, the achieved accuracy of 80.6% is rather low compared to the state of the art.

Despite the potential benefits of using machine learning and deep learning algorithms for maize crop disease identification, there is still a need for more efficient and resource-friendly models that can be implemented in low-resource settings. While some existing models have achieved good accuracy, they often require large amounts of computational power, memory, and data storage, making them impractical for use in resource-constrained environments.

This paper proposes a computation-efficient model, in alignment with (Arun and Umamaheswari, 2023), to identify crop diseases through features extraction, classification and parameters optimization. The proposed model achieves a high accuracy and moderate computation cost compared to the state of the art models.

4 PROPOSED MULTILAYER CNN MODEL

Instead of manually extracting features, CNNs can learn more advanced features from an input image. The performance of traditional feature extraction methods is inferior to that of automatic feature extraction (Liu et al., 2020). This section presents an efficient and effective ML-CNN-based model architecture, as shown in Figure 1, for features extraction and classification of maize crop images. The proposed ML-CNN comprises a five-level and 17-layer model where convolutional layer is the most important layer of the network used for feature extraction. Our ML-CNN adopts VGGNet with smaller 3x3 convolutional filters instead of larger convolutional filters such as 5x5 and 7x7. This is because a smaller filter with fewer parameters will have the same effect as a larger one. As a result, while maintaining high accuracy, the model enables faster features extraction because the reduced number of parameters.

Assuming the model's input layer $m-1$, input feature map Y^{m-1}, convolutional kernel Ck^m, the output of the convolutional layer is Om and bias b^m. In the convolutional layer, the output is calculated by convolving the input feature map with the convolution kernel and adding bias, as shown in the equations (1) and (2). The output is passed into the next layer, which is the max-pooling layer.

$$O^m_{u,v} = \sum_{i=-\infty}^{\infty} \sum_{j=-\infty}^{\infty} Y^{m-1}_{i+u,j+v}.Ck^m.y(i,j) + b^m \tag{1}$$

$$y(i,j) = \begin{cases} 1 & 0 \leq i,j \leq n \\ 0 & otherwise \end{cases} \tag{2}$$

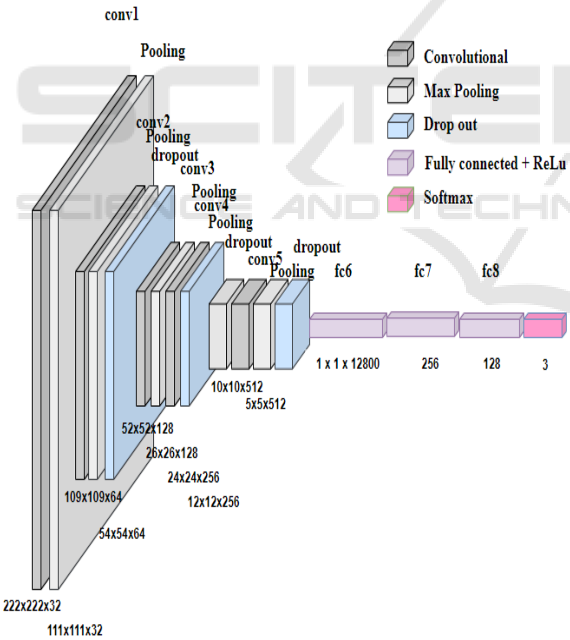


Figure 1: Proposed ML-CNN Architecture.

The first convolutional layer has 32 filters of size 3 x 3, and one max-pooling layer with a window of 2x2 size. This represents the first level of the ML-CNN network. The second convolutional layer with 64 3x3-sized filters, one max-pooling layer, and one dropout layer with 0.2% forms the second level of the network. The third level is composed of a convolutional layer, having 128 filters of size 3x3, and one max-pooling layer having a window of size 2x2. The fourth convolutional layer with 256 3x3 filters, one max-pooling layer, and one more layer of dropout with 0.2% has been added to form the fourth level of the ML-CNN network. The fifth level of the network consists of one more convolutional layer with 512 filters with 3x3 size, one 2x2 max-pooling layer and another dropout layer with 0.5% of dropout of neurons. A flattening layer (*fc6*) converts the input data from the convolution layer (*conv5*) into a vector. This process is often referred to as ”flattening” the data. Thereafter, a dense layer (*fc7*) with 256 neuron, ReLu as an activation function is used for linear transformation so that when the outcome is below 0, ReLu does not activate the Neurons which reduces the computations. Finally, another denser layer (*fc8*) with 128 neurons and ReLu as an activation function has been added following the application of a dropout layer with 0.2%. The last layer applies Softmax with three neurons, as we have three classes for classification. The probabilities of every class and target class are computed using the softmax activation function, which ranges from 0 to 1.

The target class for the given input is then determined using the cascade of the 5 levels and a sparse categorical cross-entropy as a loss estimation function. The model has been implemented with a batch size of 32, an input image size of 224x224, an activation function referred to as ”ReLU” at the dense layer, a function referred to as ”softmax” at the classification layer, an optimizer referred to as ”Adam” keeping a learning rate of 0.0001, and filter size of 3x3 at each convolutional layer.

Current crop disease image identification mainly involves the use of pre-trained highly-parameterized CNNs. However, these fine-tuned networks tend to have high complexity due to many parameters, as they are trained on a large dataset containing a lot of information, leading to high bias and low accuracy. This challenge is tackled in our ML-CNN by having a simpler structure, lower complexity and fewer parameters as it is trained on a task-specific dataset. Furthermore, using 3x3 convolutional kernels increases the receptive field of view and decreases the number of parameters in the network, which leads to low bias and high accuracy. This has led to achieve the highest accuracy level at 31 epochs. Table 1 shows the hyperparameter of the proposed model.

Convolutional Layers. The primary method for extracting features from input images is convolution. A convolution window can be mapped onto a 2-D image to calculate 2-dimensional convolution and obtain the corresponding convolution value by multiplying the

Table 1: Hyper-parameter for Proposed ML-CNN.

Dataset	7:2:1 ratio for train, valid, and test
Pre-processing	Resizing at 224x224 pixels
Learning rate	0.0001
Epochs	200
Optimizer	ADAM
Batch size	32
Loss Function	Sparse categorical cross-entropy

input with a convolution filter (kernel). The convolution outcome is a feature map having a shape computed using Equation 3.

$$(n+2p-f+1)/s*(n+2p-f+1)/s*3 \tag{3}$$

Where n represents the input image size, p shows padding, f means the size of the filter, and s is stride. 3 represents the three channels “RGB.”

Max-Pooling Layers. Max pooling is a down-sampling operation that reduces computational costs and enhances spatial invariance in an image by selecting the maximum value among the elements covered by the kernel. It summarizes the features produced by the convolution layer.

Dropout Layer. The primary objective of employing a dropout layer is to enhance the trained model's prediction performance. During the training phase, ignoring neurons of a randomly selected set is referred to as a dropout. All neurons are used during the testing phase but are scaled by factor p.

Fully Connected Layers. A fully connected layer transforms the outputs of the preceding layer into a single vector, ”flattening”, that can serve as an input for the subsequent stage in the ML-CNN. The last layer of our ML-CNN uses the softmax activation function to calculate the probability of each class from the hidden layers. Our classification model can have multiple fully connected layers added depending on how deep the architecture can be, however this would require larger and diverse dataset for training and high computation cost for testing.

ReLU Activation Function. It refers to the Rectified linear unit and primarily implemented within the neural network's hidden layers. ReLU function activates multiple layers of neurons to back-propagate the errors. We chose the ReLu function because it requires fewer mathematical operations compared to Tanh and Sigmoid, so that to achieve less computation cost. Furthermore, in our ML-CNN, the network is sparse with only a few neurons activated at once depending on the linear transformation, or no neuron is activated if the linear transformation is below or equal 0 as shown in Equation (4), making it efficient and simple to compute.

$$A(x) = max(0,x) \tag{4}$$

5 DATASET AND PROCESSING

It is essential to collect a large number of plant images to achieve a highly accurate classification of maize crop diseases. For the proposed ML-CNN, the maize crop dataset is composed of images from the PlantVillage database (GHOSE, 2022) and OSF (Wiesner-Hanks and Brahimi, 2022). Table 2 shows the hardware configuration and software resources used for the training.

Table 2: HW and SW resources used for training.

Units	Parameters
System	NVIDIA-SMI 460.32.03
Graphics processor unit	Tesla T4
RAM	32GB
Environment	Google Colab pro
Framework	Keras with TensorFlow
Operating system	Windows 10
Programming language	Python

5.1 Dataset

In general, datasets on agricultural concerns are not widely accessible, and real-time images are a key concern (Redmon and Farhadi, 2018). We acquired the maize crop dataset from PlantVillage (GHOSE, 2022) and OSF (Wiesner-Hanks and Brahimi, 2022). Each image is taken on a solid background, with a single leaf in a controlled environment. The dataset consists of two disease classes along with the healthy class. Two important agricultural diseases that affect the maize crop, namely Northern leaf blight (NLB) and Common Rust, were considered. Most commonly, plants infected with common rust produce brown pustules on the surface of their leaves. The infection also spreads to the sheaths and other parts of the plant. Lesions of northern corn leaf blight first appear on the plant's lower parts, then spread to the plant's entire leaves, where they turn a pale gray as they grow. The dataset description is given in Table 3. We divide the dataset into three sets of data: train set, validation set and test set, which represented 70% and 30%, and 10%, respectively of the total images. Some sampled images from the dataset are shown in Figure 2.

Table 3: Maize crop dataset description.

Category	No of Samples
Northern leaf blight (NLB)	1146
Common Rust	1306
Healthy	1162

(a) NLB (b) Common Rust (c) Healthy

Figure 2: Sample images from the dataset.

5.2 Data Processing

We performed image processing steps on the dataset images, including image augmentation, pre-processing and resizing.

Image Augmentation. Image augmentation refers to transforming input image samples by minor rotations, reflections, flips zooming, scaling and shifting. As a result, data augmentation enhances the dataset by increasing the number of training samples which can significantly improve deep CNN's efficiency.

- Rotation: it rotates a training image at random through different angles.
- Shear: it adjust the shearing range. We adopted a shearing of 0.2.
- Brightness: it aids the model in adjusting to changes in lighting by feeding images of varying brightness during training.
- Flip: an image can be flipped at different positions.

Image Pre-Processing. In image pre-processing, digital images are processed before being fed into computer vision algorithms for further processing. The pre-processing of images improves the quality of input data, enhances particular image features, or extracts meaningful information from images. In our case, the pre-processing reduces the blurriness and noise in input images.

As part of the pre-processing, to speed up the convolution and classification operations, we first resize the input samples to 224 x 224 pixels.

6 RESULTS AND DISCUSSION

This section presents the analysis results of the detection of maize crop diseases using our ML-CNN model. The dataset was divided into three classes: healthy and two diseases with a total number of 6940 input image samples (after augmentation).

6.1 Accuracy

Table 4 depicts a comparison of the train accuracy, test accuracy, train loss and test loss of state of the art pre-trained deep learning models such as InceptionV3, VGG16, VGG19, and ResNet50 with our ML-CNN model. The result demonstrates that our ML-CNN model outperforms the conventional classifiers in terms of identification accuracy. Furthermore, the proposed ML-CNN improved identification accuracy by 16.32%, 1.48%, 1.28%, and 2.26%, respectively. One can see as well that our ML-CNN achieves the best testing accuracy of 98.16% while exhibiting lower training, and testing loss of 0.0097% and 0.0943%.

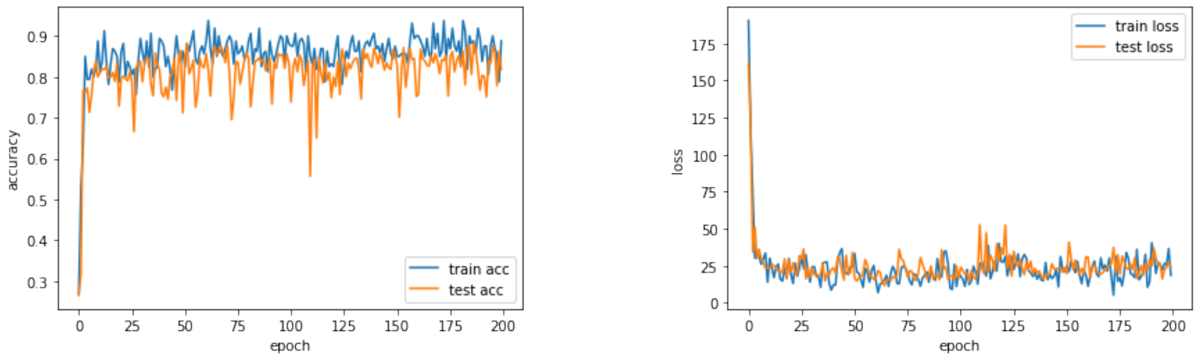
Table 4: Training accuracy, test accuracy, training loss, and test loss of InceptionV3, VGG16, VGG19, ResNet50, and Proposed ML-CNN.

Algorithm	Train Acc	Train Loss	Test Accu	Test Loss
InceptionV3	88.75%	18.56	81.84%	24.5
VGG16	98.75%	0.21	96.68%	1.1
VGG19	98.12%	0.47	96.88%	1.6
ResNet50	98.75%	0.20	95.90%	1.7
ML-CNN	99.60%	0.009	98.16%	0.09

Accuracy and loss of both training and test for InceptionV3, VGG16, VGG19, ResNet50 and proposed ML-CNN are depicted in Figure 3, Figure 4, Figure 5, Figure 6 and Figure 7 respectively.

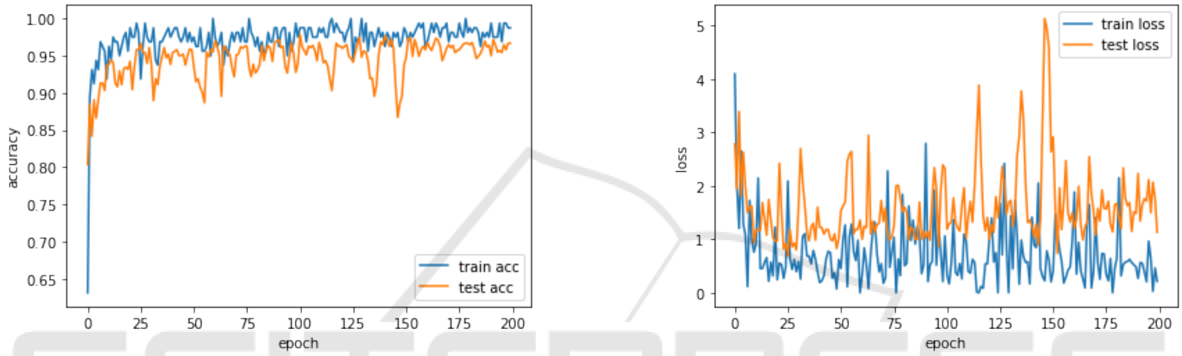
The x-axis labeled with the number of epochs can be seen as the number of times the algorithm will learn from the complete dataset. The y-axis shows the models accuracy. Our proposed model achieves better testing accuracy of 98.16% than other models such as InceptionV3, VGG16, VGG19 and ResNet50, gaining 81.84%, 96.68%, 96.88%, 95.90% test accuracy respectively. Meanwhile, our ML-CNN achieved a minimum loss of 0.0943%.

Figure 8 presents a training accuracy comparison between InceptionV3, VGG16, VGG19, and, ResNet50 with our proposed ML-CNN algorithm. Similarly, the testing accuracy of InceptionV3, VGG16, VGG19, and ResNet50 compared to the proposed ML-CNN algorithm is depicted in Figure 9. One can see from both figures that the proposed ML-CNN outperforms the considered state of the art alter-



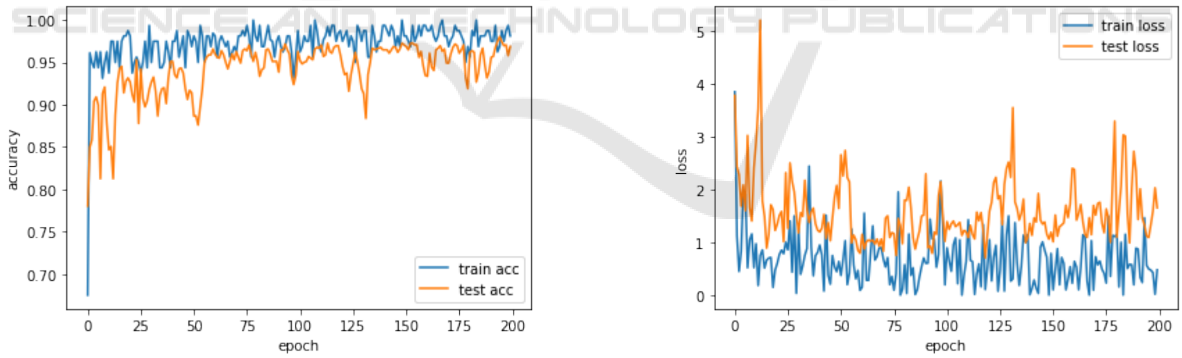
(a) InceptionV3 Accuracy (b) InceptionV3 Loss

Figure 3: Training and Test Accuracy of InceptionV3.



(a) VGG16 Accuracy (b) VGG16 Loss

Figure 4: Training and Test Accuracy of VGG16.



(a) VGG19 Accuracy (b) VGG19 Loss

Figure 5: Training and Test Accuracy of VGG19.

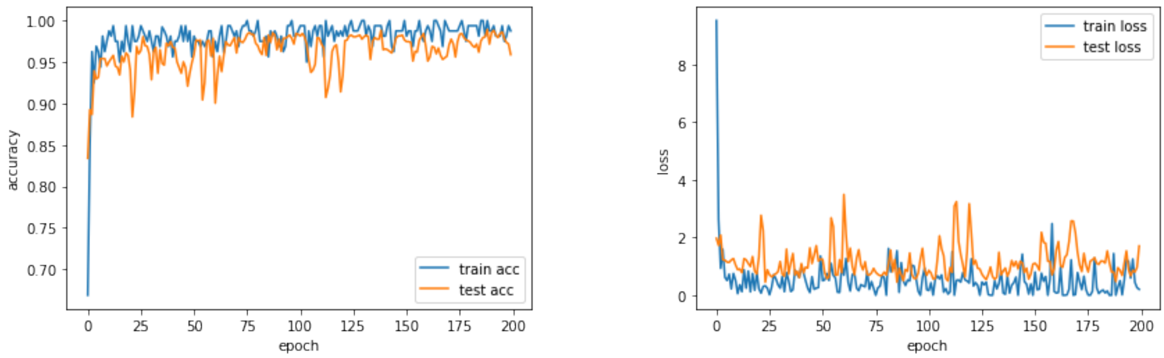
natives for both training and testing accuracy.

6.2 Precision, Recall, and F1-Score

Classification tasks use precision, recall and F1-score as metrics for evaluation. True positive predictions are measured by precision among all positive predictions, while the recall measures actual positive predictions.

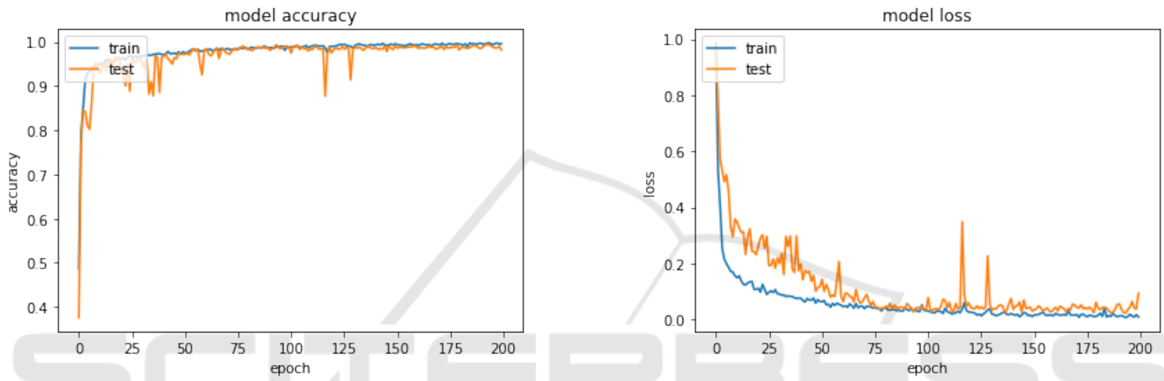
F1-score is a balanced method of calculating precision and recall. Macro averaging involves calculating each class's metric separately and unweighting the mean. The weighted average takes the average of all classes, where the weight is the number of samples in each class. It can be useful when the different classes have different sizes, and one needs to assign much more weight to larger classes.

Figure 10 shows precision, recall, F1-score, macro



(a) ResNet50 Accuracy (b) ResNet50 Loss

Figure 6: Training and Test Accuracy of ResNet50.



(a) ML-CNN Accuracy (b) ML-CNN Loss

Figure 7: Training and Test Accuracy of the Proposed ML-CNN.

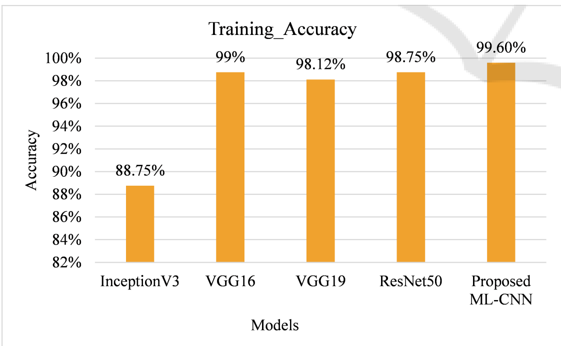


Figure 8: Training Accuracy Comparison of InceptionV3, VGG16, VGG19, and ResNet50 with our proposed ML-CNN.

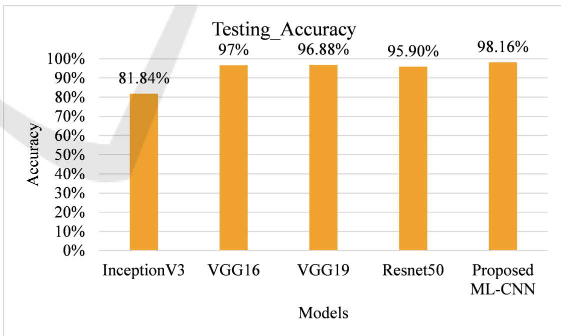


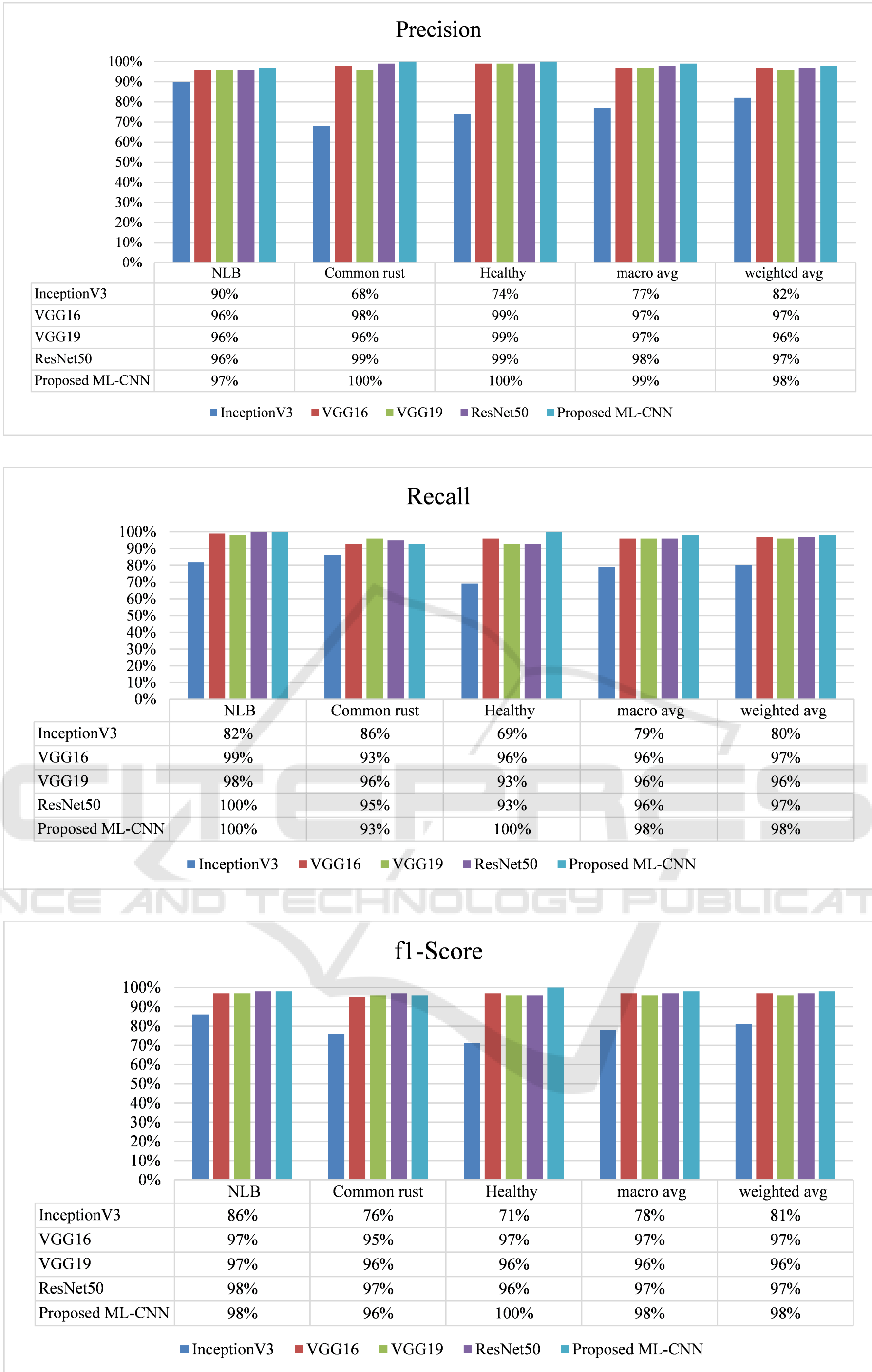
Figure 9: Testing Accuracy Comparison of InceptionV3, VGG16, VGG19, and ResNet50 with our proposed ML-CNN.

average value, and weighted average of each class for InceptionV3, VGG16, VGG19, ResNet50, and proposed ML-CNN.

Clearly, the proposed ML-CNN model outperforms the state of the art models evaluated in this study with exceptional scores in precision, recall, F1-score, macro average, and weighted average.

6.3 Confusion Matrix

The confusion matrix is widely used for analyzing classification models performance. The model's predictions are presented in a tabular format, displaying the number of true positive predictions, true negative predictions, false positive predictions, and false negative predictions. Figure 11 depicts the confusion matrix for InceptionV3, VGG16, VGG19, ResNet50,



Precision	NLB	Common rust	Healthy	macro avg	weighted avg
InceptionV3	90%	68%	74%	77%	82%
VGG16	96%	98%	99%	97%	97%
VGG19	96%	96%	99%	97%	96%
ResNet50	96%	99%	99%	98%	97%
Proposed ML-CNN	97%	100%	100%	99%	98%

Recall	NLB	Common rust	Healthy	macro avg	weighted avg
InceptionV3	82%	86%	69%	79%	80%
VGG16	99%	93%	96%	96%	97%
VGG19	98%	96%	93%	96%	96%
ResNet50	100%	95%	93%	96%	97%
Proposed ML-CNN	100%	93%	100%	98%	98%

f1-Score	NLB	Common rust	Healthy	macro avg	weighted avg
InceptionV3	86%	76%	71%	78%	81%
VGG16	97%	95%	97%	97%	97%
VGG19	97%	96%	96%	96%	96%
ResNet50	98%	97%	96%	97%	97%
Proposed ML-CNN	98%	96%	100%	98%	98%

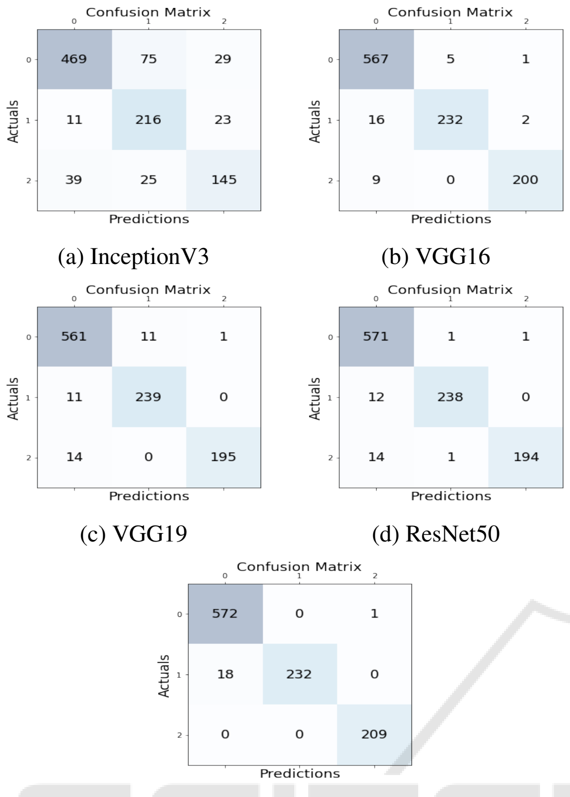
Figure 10: Precision, recall F1-score for InceptionV3, VGG16, VGG16, ResNet50 and Proposed ML-CNN.

and proposed ML-CNN.

The proposed ML-CNN shows a high level of accuracy. This is evident by the concentration of accuracy on the diagonal- and the high prediction accuracy for the three classes. This performance is superior to that of the other pre-trained models, indicating that ML-CNN offers excellent identification results.

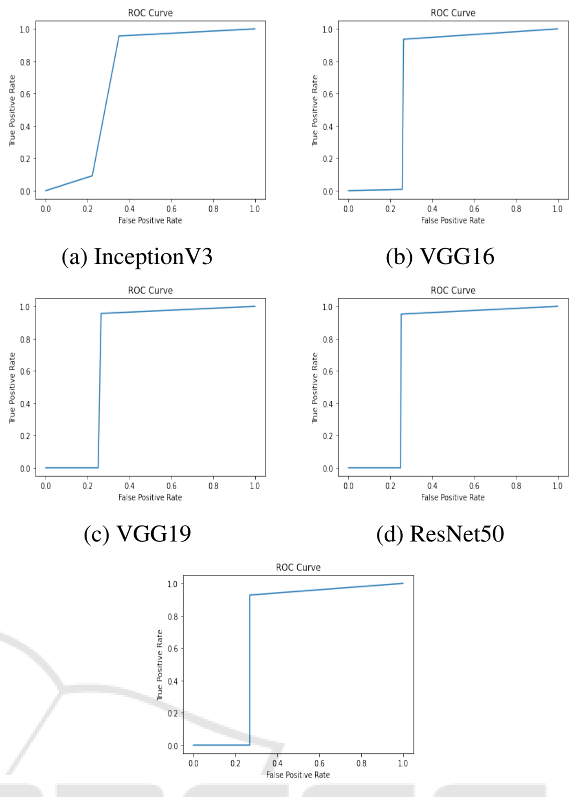
6.4 ROC-AUC

The proposed ML-CNN was evaluated using the Receiver Operating Characteristic (ROC) function. ROC



(a) InceptionV3 (b) VGG16 (c) VGG19 (d) ResNet50 (e) Proposed ML-CNN

Figure 11: Confusion Matrix of InceptionV3, VGG16, VGG16, ResNet50 and Proposed ML-CNN.



(a) InceptionV3 (b) VGG16 (c) VGG19 (d) ResNet50 (e) Proposed ML-CNN

Figure 12: ROC curves for InceptionV3, VGG16, VGG19, ResNet50, and Proposed ML-CNN.

for InceptionV3, VGG16, VGG16, ResNet50, and Proposed ML-CNN are illustrated in Figure 12.

Figure 13 shows the area under the curve for InceptionV3, VGG16, VGG19, ResNet50 and our ML-CNN of the NLB, common rust and, healthy leaves. According to the findings, the proposed ML-CNN achieved an AUC of 98% for NLB, 96% for common rust, and 100% for healthy leaves, and a strong ability to distinguish between positive and negative cases. In general, this demonstrates the efficacy of the proposed ML-CNN model in identifying and classifying the target variable with high precision.

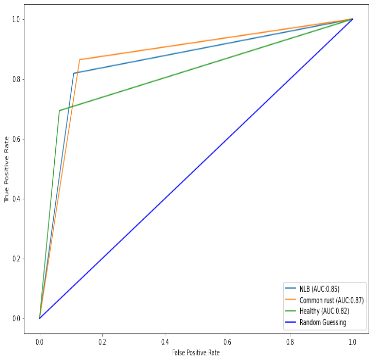
6.5 Feature Visualization

CNNs use raw image pixels to learn abstract concepts and features. Activation maximization is used to show the learned features in feature visualization. Figure 14 depicts the feature visualization when an input image of Northern leaf blight is fed to the trained network. The first ML-CNN layer extracts an image's low-level features like edges, blobs and orientation. Features like more intricate patterns and textures are learned in 2nd convolutional layers. In the 3rd layer, the filters learn to detect more complex combinations of edges and textures that are specific to certain objects or parts of an object. In the 4th layer, the filters learn abstract patterns such as the parts of an object or the presence of specific objects in the image. The final convolutional layer learns features like entire objects. The fully connected layers learn to link activation from high-level features to predicted classes.

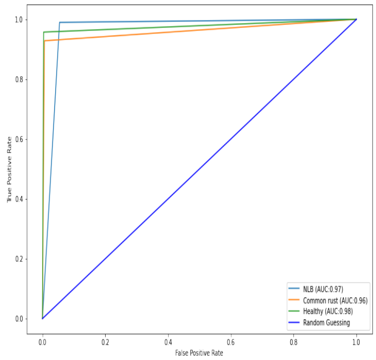
7 CONCLUSIONS

In this paper, an efficient model based on a deep convolutional neural network was proposed to classify healthy and diseased maize crop leaves. A total of 5,487 training, 965 validation, and 488 test images (after augmentation) were collected from the PlantVillage dataset. Northern leaf blight (NLB), Common rust, and healthy images are included in this dataset.

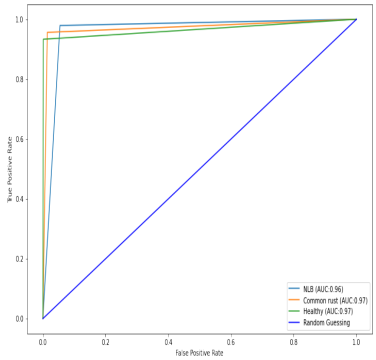
Compared to the state of the art pre-trained CNN models such as InceptionV3, VGG-16, VGG19 and ResNet50, our ML-CNN model improved identification accuracy by 16.32%, 1.48%, 1.28%, and 2.26%



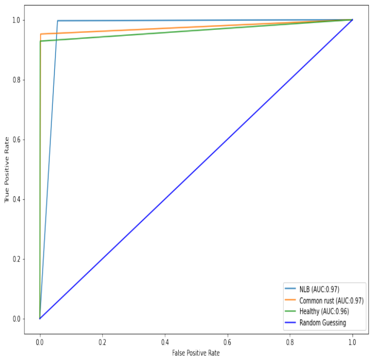
(a) InceptionV3



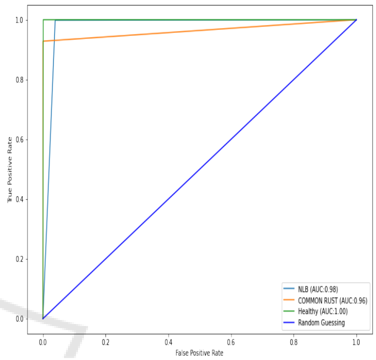
(b) VGG16



(c) VGG19



(d) ResNet50



(e) Proposed ML-CNN

Figure 13: AUC of InceptionV3, VGG16, VGG16, ResNet50 and Proposed ML-CNN.

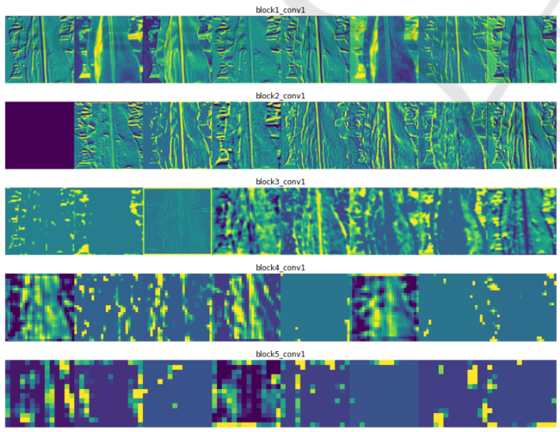


Figure 14: Visual representation of each Convolution Layer.

respectively, and achieved a much better test and train accuracy of 99.60%, and 98.16%, respectively. Globally, the proposed ML-CNN was proven to be efficient by a large number of our experiments including precision, f1-score, recall, and AUC-ROC.

The proposed ML-CNN not only achieves high accuracy but also significantly reduces the computational cost and memory footprint, making it a promising solution for embedded systems. This feature enables the model to be utilized in devices with limited resources, such as drones or smartphones, allowing farmers to identify crop diseases in real time.

As a future work, we plan to extend the set of features to be identified to detect multiple diseases on a single maize leaf and estimate their severity. Additionally, a user-friendly mobile application will be developed to aid farmers in identifying crop diseases as early as possible.

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