LCNET: LIGHTWEIGHT CONVOLUTIONAL NEURAL NETWORK FOR CORN LEAF DISEASE CLASSIFICATION

एलसीनेट: मकई पत्ती रोग वर्गीकरण के लिए हल्का संवादात्मक तंत्रिका नेटवर्क

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ABSTRACT
Crop diseases significantly diminish agricultural production, resulting in economic losses. Early detection and species identification remain major challenges. This paper introduces a lightweight Convolutional Neural Network (LCNet) designed for the detection of corn diseases, including blight, common rust, and gray leaf spot, using an efficient, low-latency model. The suggested architecture consists of three convolutional layers, three pooling layers, and one fully linked layer. Experimental findings indicate that LCNet surpasses the pre trained architecture MobileNetV2, DenseNet201, ResNet50, and different past study with an average accuracy of 94.65%. This method enables prompt disease identification, assisting farmers in averting significant crop losses while minimizing human labor in oversight and administration.

ABSTRACT IN HINDI (हिन्दी)
फसल की बीमारियाँ कृषि उत्पादन को काफी कम कर देती हैं, जिसके परिणामस्वरूप आर्थिक नुकसान होता है। इनका शीघ्र पता लगाना और प्रजातियों की पहचान प्रमुख चुनौतियाँ बनी हुई हैं। यह पेपर एक हल्के कन्वोल्यूशनल न्यूरल नेटवर्क (एलसीनेट) का परिचय देता है, जिसे एक कुशल, कम-विलंबता मॉडल का उपयोग करके ब्लाइट, सामान्य जंग और ग्रे लीफ स्पॉट सहित मकई रोगों का पता लगाने के लिए डिज़ाइन किया गया है। सुझाई गई वास्तुकला में तीन संकेंद्रित परतें, तीन पूलिंग परतें और एक पूरी तरह से जुड़ी हुई परत शामिल हैं। प्रायोगिक निष्कर्षों से पता चलता है कि एलसीनेट 94.65% की औसत सटीकता के साथ पूर्व प्रशिक्षित आर्किटेक्चर मोबाइलनेट वी2, डेंसनेट201 रेसनेट50, और विभिन्न पिछले अध्ययनों से आगे निकल जाता है। यह विधि शीघ्र रोग की पहचान करने में सक्षम बनाती है, जिससे किसानों को फसल के महत्वपूर्ण नुकसान को रोकने में सहायता मिलेगी जबकि निरीक्षण और प्रशासन में कम से कम मानव श्रम की आवश्यकता होगी।

INTRODUCTION

The fast proliferation of plant diseases manifests an alarming risk to global crop production, especially for staple crops such as corn, which is a fundamental food supply for millions globally (*Khan et al., 2024*). Traditional disease detection approaches, dependent on human field inspections, are both time-intensive and deficient in the precision required for early-stage diagnosis (*Hossain et al., 2023*). Recent breakthroughs in artificial intelligence and deep learning have enabled the creation of automated, high-precision models for plant disease categorization, therefore markedly improving early detection capabilities (*Hassan et al., 2021*). Convolutional Neural Networks (CNNs) have become the predominant method owing to its capacity to extract hierarchical characteristics from leaf pictures, facilitating the recognition of intricate disease patterns *(Li et al., 2021*). CNNs have emerged as a preeminent method in image-based illness classification, owing to its capacity to acquire hierarchical information, hence enhancing both accuracy and dependability. Several CNN architectures, including MobileNetV2 (*Sandler et al., 2018a*), ConvNet (*Liu et al., 2022*), and EfficientNet (*Howard et al., 2017*) etc. have been applied in previous research to detect and classify plant diseases with high precision. Recent research was used CNN-based deep learning models to improve the categorization of plant leaf diseases. In their study, *Amin et al., (2022*) suggested an end-to-end deep learning system for the detection of corn leaf diseases. Their methodology used two pre-trained convolutional neural networks, EfficientNetB0 and DenseNet121, to derive deep feature representations from corn leaf photos. The retrieved features were concatenated to build a more informative feature set, enhancing model performance. Moreover, data augmentation methods were used to enhance the variety of training samples.

The model was trained and evaluated using the PlantVillage dataset, with an exceptional classification accuracy of 98.56%, surpassing other models such ResNet152 (98.37%) and InceptionV3 (96.26%). Similarly, *Khan et al., (2024*), examined the use of deep transfer learning for the fine-grained categorization of corn leaf diseases. They used four pre-trained deep learning architectures-VGGNet, InceptionV3, ResNet50, and InceptionResNetV2-to identify complex disease patterns in corn leaves. ResNet50 demonstrated exceptional performance, with a validation accuracy of 87.51%, a precision of 90.33%, and a recall of 99.80%, underscoring its proficiency in precise illness detection. This research highlights the capability of deep learning methodologies in enhancing plant disease categorization, facilitating the development of more effective and efficient diagnostic models.

This research presents a LCNet developed for the classification of corn leaf diseases, based on recent advancements. The proposed model improves computational efficiency with a streamlined architecture of three convolutional layers, three pooling layers, and one fully connected layer, therefore significantly reducing the number of trainable parameters while maintaining satisfactory classification accuracy. The key contributions of this study lie in the development of a lightweight CNN-based model specifically designed for the detection of corn leaf diseases, which are summarized as follows:

1. Develop a compact and Lightweight CNN model tailored for the detection of corn diseases such as blight, common rust, and gray leaf spot.
2. The architecture comprising three convolutional layers, three pooling layers, and a fully connected layer to achieve a balance between accuracy and computational efficiency.
3. Achieve superior classification performance with LCNet, outperforming models like MobileNetV2, DenseNet201, and ResNet50, with an average accuracy of 94.65%.
4. Facilitate early and precise identification of crop diseases, aiding farmers in preventing major yield losses while reducing reliance on manual monitoring.
5. Conduct thorough experimental evaluations and comparative studies to validate the proposed model's effectiveness against established deep learning approaches.

The remainder of this paper is organized as follows: The next section provides a review of related studies. The subsequent section details the datasets, methodology, and research framework. Following this, the experimental results are presented and compared with previous works. Lastly, the final section summarizes the conclusions and outlines potential future research directions.

LITERATURE SURVEY

Recent years have seen considerable interest in the early identification and categorization of agricultural diseases with deep learning methods. Conventional techniques for disease diagnosis, including physical examination by agricultural specialists, are often time-consuming, labor intensive, and susceptible to inaccuracies. Researchers have investigated numerous CNN-based algorithms for automated illness diagnosis to tackle these problems. Notable designs, such MobileNetV2 (*Howard et al., 2017*), EfficientNet (*Tan et al., 2019*), and ConvNet *(Liu et al., 2022*) etc. have been widely used owing to their superior accuracy and resilience. Nonetheless, these models sometimes entail substantial computing expenses, rendering them less appropriate for real-time applications in resource-limited agricultural settings.

The article written by *Prasetyo et al., (2023*), focuses on classifying corn plant leaves to distinguish healthy leaves from three disease types: Northern Leaf Blight, Common Rust, and Gray Leaf Spot, using a CNN model based on the ResNet-9 architecture to develop a strong classification system. The dataset included 9,145 photos, allocated into 80% for training and 20% for testing. The researchers performed an epoch comparison to ascertain the ideal model performance across five values: 5, 25, 55, 75, and 100 epochs. The optimal accuracy was attained after 100 epochs, which was then used for the final model training. Furthermore, hyperparameter tweaking experiments were conducted, concentrating on the number of workers (num_workers = 4) and batch size (batch_size = 32), which enhanced the model's performance. The final model had a classification accuracy of 99%. The research study done by *Rachmad et al., (2023*), examined the use of CNN for the early identification and categorization of corn illnesses, with the objective of reducing production losses in Indonesia, a nation heavily reliant on corn. The research used a collection of corn leaf photos gathered from agricultural areas in the Madura Region, focusing on four categorization categories: healthy, gray leaf spot, blight, and common rust. A variety of CNN designs, such as SqueezeNet, AlexNet, ResNet-101, ResNet-50, and ResNet-18, were assessed for their efficacy in illness categorization.

The research used Adam optimization with a learning rate of 0.0001, training models for five epochs with 100 iterations, and implemented a 70:30 division for training and testing. Among the evaluated designs, ResNet-50 exhibited exceptional performance, with an accuracy of 95.59%. These results underscore the capability of CNN-based models in automating corn disease identification, enabling early intervention to reduce agricultural losses.

Ariska et al., (2024), investigated the use of CNN for the automated categorization of corn leaf diseases, using a dataset of 2,145 photos of leaf blight and 1,574 images of leaf spot, capitalizing on the network's capacity to extract and integrate local features for efficient disease detection. The model attained a remarkable classification accuracy of 99%, culminating in a final training accuracy of 99.06% and a validation accuracy of 98.50%. The research proposes further improvements by integrating contemporary architectures like EfficientNet B3 with transfer learning or MobileNet to boost accuracy and processing efficiency. These results highlight the efficacy of CNN-based solutions in precision agriculture, enabling early disease identification and enhanced crop management tactics. *Waheed et al., (2020*), examined the worldwide importance of corn and the adverse effects of diseases such as common rust, gray leaf spot, and northern corn leaf blight, highlighting the need for accurate and prompt disease identification to enhance crop output and quality. The suggested DenseNet model attained an impressive accuracy of 98.06%, surpassing conventional Convolutional Neural Network (CNN) designs like EfficientNet, VGG19Net, NASNet, and Xception Net, while using less parameters. This efficiency indicates the model's applicability for real-time use in agricultural contexts. The research highlights the effectiveness of enhanced deep learning models in diagnosing agricultural diseases, facilitating more sustainable and productive farming methods.

The investigation done by *Ahila Priyadharshini et al., (2019)*, presents a deep learning methodology using a modified LeNet architecture for the categorization of corn leaf diseases. The proposed CNN model is trained on corn leaf images from the PlantVillage dataset, differentiating among four categories: three disease classifications and one healthy category. The experimental findings indicate the model's efficacy, with an accuracy of 97.89%. These results underscore the efficacy of deep learning in agricultural disease diagnosis, providing an economical and precise option for automated crop health monitoring. The work underscores the significance of CNN-based models in precision agriculture, establishing a basis for future research on the optimization and implementation of these systems in practical agricultural contexts. The paper of *Zhang et al., (2021),* presents a CNN model enhanced with a Multi-Activation Function (MAF) module to improve detection accuracy for corn illnesses. Considering the constraints posed by limited illness datasets, the study employs image preprocessing methods to facilitate data augmentation. Furthermore, transfer learning and a warm-up training technique are used to expedite the learning process. The suggested model effectively identifies three corn diseases-maculopathy, rust, and blight-attaining a validation accuracy of 97.41%. To evaluate the efficacy of the MAF module, baseline testing and ablation experiments were performed on many CNN architectures. The findings indicate that the incorporation of the MAF module significantly enhances CNN performance, with optimal results achieved by the amalgamation of Sigmoid, ReLU, and Mish activation functions on ResNet50, resulting in a 2.33% increase in accuracy. The results illustrate the efficacy of optimized CNN models in agricultural contexts, providing a dependable and efficient method for automated corn disease identification.

MATERIALS AND METHODS

The present study adopts a deep learning-based methodology for the automated detection of corn leaf diseases using a lightweight Convolutional Neural Network (LCNet). The proposed framework involves several key stages, including data acquisition, preprocessing, dataset partitioning, model design, training, and performance evaluation (Fig. 1). A diverse set of corn leaf images representing diseases such as blight, common rust, and gray leaf spot was utilized to ensure accurate classification. The LCNet architecture was specifically designed to be computationally efficient, incorporating multiple convolutional and pooling layers to extract relevant features while maintaining low-latency predictions (Fig. 2). The model's performance was benchmarked against well-known deep learning models such as MobileNetV2, DenseNet201, and ResNet50. Standard evaluation metrics accuracy, precision, recall, and F1-score were employed to assess the model's effectiveness. Developed using deep learning frameworks, the experimental results demonstrated that LCNet achieved superior classification accuracy with reduced computational overhead, making it a suitable candidate for real-time deployment in agricultural environments.

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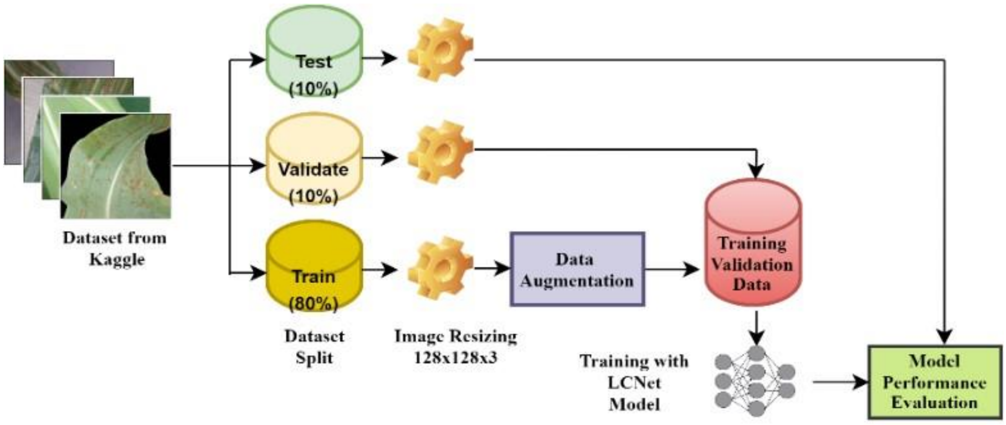


Fig. 1 - Proposed Methodology for CNN based Corn Leaf Disease Classification

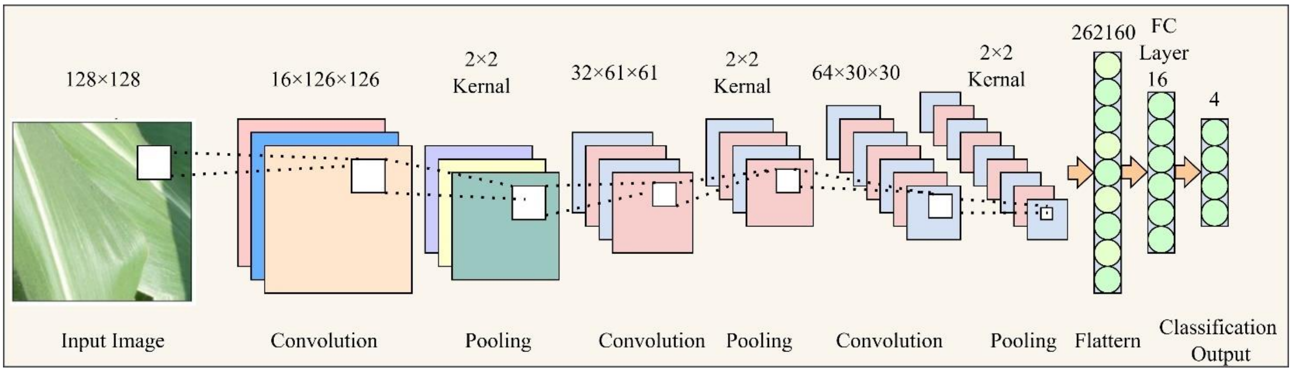


Fig. 2 - Proposed LCNet Model

A. Datasets:

The suggested LCNet model along with existing deep learning architectures, namely MobileNetV2, DenseNet201, and ResNet50, was trained and assessed using a dataset of corn leaf images. These models were employed to classify and identify diseases in previously unseen images. This work used a dataset of 4,188 corn leaf images obtained from Kaggle, classified into four categories: three disease types-common rust, gray leaf spot, and blight-and one healthy category.

To standardize input dimensions, the pictures were scaled to 128×128 pixels for the proposed CNN model. Pixel values were normalized by dividing each by 255, facilitating network weight initialization and enhancing model convergence during training. To facilitate efficient model training and assessment, the dataset was partitioned into training, validation, and testing subsets with an 80:10:10 distribution, a strategy derived from *Sahu et al., (2021*). As a result, 3,348 photos were designated for training, 419 for validation, and 421 for testing. The distribution of the corn dataset is clearly illustrated in (Figs. 3-4). This organized data segmentation enabled effective model training, reducing overfitting and ensuring the model generalizes well to new data. This technique seeks to provide an efficient and precise corn disease detection system with enhanced computing performance.

B. Transfer Learning via popular deep learning pre-trained models:

Training a network from scratch requires a lot of time and resources. Transfer learning is one of the solutions to this problem. It is a set of techniques rather than a single strategy (*Atila et al., 2021*), in which certain pre-trained network weights are employed during training, to handle different problems. According to the requirement of the new problem, the bottom layer of the trained model was replaced by a new layer.

ResNet50: TheResNet50 is a deep convolutional neural network model developed to tackle the difficulties associated with training very deep networks, especially the vanishing gradient issue. It belongs to the Residual Network (ResNet) family, proposed by *He et al., (2016)*, and has 50 layers, making it very efficient for picture classification and identification applications. The fundamental novelty of ResNet50 is its implementation of residual learning via skip connections, enabling information to circumvent certain levels and directly reach deeper layers. This approach guarantees that deeper networks may be trained effectively without experiencing performance deterioration. The ResNet50 design comprises convolutional layers, batch normalization, ReLU activation, pooling layers, and fully connected layers, with residual blocks crucial for ensuring steady gradient propagation. Each residual block has three convolutional layers (1×1, 3×3, and 1×1), which enhance feature extraction and facilitate dimensionality reduction. ResNet50 utilizes identity mappings to facilitate the learning of intricate patterns while ensuring computational efficiency. One significant feature of ResNet50 is its capacity to attain high accuracy in picture classification tasks while incurring comparatively lower computing expenses than deeper models. It has been extensively used in medical image analysis, object identification, autonomous driving, and transfer learning because of its proficiency in generalizing across diverse domains. ResNet50, pre-trained on extensive datasets such as ImageNet, may be fine-tuned for applications, making it a potent and versatile instrument for diverse computer vision tasks.

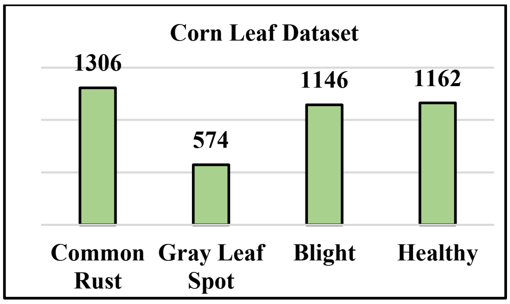
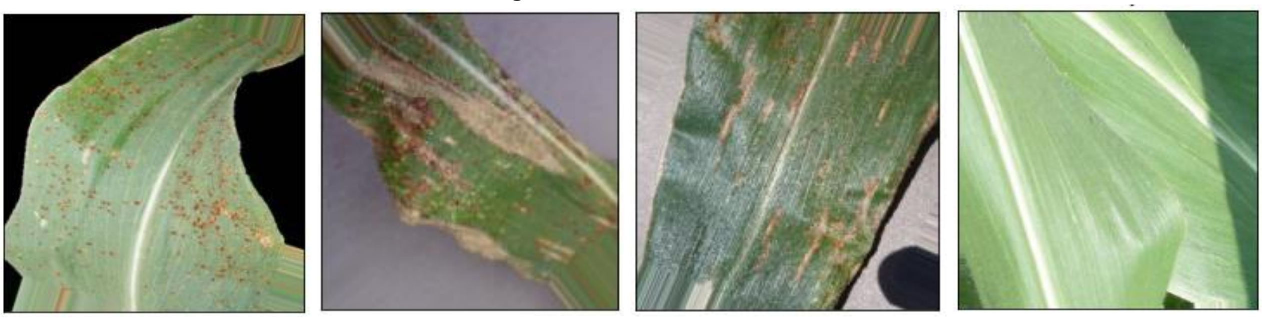


Fig. 3 - Corn Leaf Dataset



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

Fig. 4 - Image from Corn Leaf Dataset

(a) Common Rust Disease; (b) Blight Disease; (c) Gray Leaf Spot Disease; (d) Healthy images

DenseNet: This deep learning architecture was designed to enhance feature propagation and address the challenge of vanishing gradients commonly encountered in convolutional neural networks (CNNs). Introduced by *Huang et al., (2017*), DenseNet improves network performance through the implementation of dense connections, where each layer is directly connected to all subsequent layers within a dense block. Unlike traditional CNNs that follow a sequential information flow, DenseNet promotes the reuse of feature maps across layers, thereby improving gradient transmission and supporting efficient feature learning. Its structure comprises densely connected blocks separated by transition layers that incorporate batch normalization, 1×1 convolutions, and average pooling, which help regulate network complexity and reduce the number of parameters. This design leads to higher accuracy with fewer parameters compared to deeper architectures like ResNet. DenseNet is available in various configurations, such as DenseNet-121, DenseNet-169, DenseNet-201, and DenseNet-264, which indicate the number of layers. A significant advantage of DenseNet is its ability to deliver strong performance with reduced computational and memory demands, making it highly suitable for tasks like image classification, medical image processing, and object detection. Additionally, DenseNet models pre-trained on large-scale datasets like ImageNet are widely applied in transfer learning, allowing them to be fine-tuned for domain-specific problems. The model’s efficient feature reuse mechanism reduces redundancy and enhances learning capabilities, positioning it as an optimal choice for high-accuracy applications with limited computational resources.

MobileNetV2: MobileNetV2, is a streamlined and effective convolutional neural network architecture tailored for mobile and embedded applications, providing a compromise between precision and computing economy. It was introduced by (Sandler et al., 2018b), with the integration of inverted residuals and linear bottlenecks, therefore markedly enhancing performance and reducing computing complexity. The fundamental innovation of MobileNetV2 is the depth wise separable convolution, which reduces the number of parameters and computations. It preserves a streamlined architecture while attaining competitive accuracy, making it exceptionally appropriate for picture classification, object identification, facial recognition, and AI-driven mobile apps. Its efficacy facilitates implementation on low-power devices, including smartphones, IoT devices, and edge computing systems. MobileNetV2, pre-trained on extensive datasets such as ImageNet, may be fine-tuned for specific applications, enabling significant versatility across several domains. It is extensively used in deep learning applications that need rapid inference and low resource usage, owing to its optimal balance between accuracy and computational economy.

Hyper-Parameters:
Hyperparameters are crucial for enhancing the training process of deep learning models. In this study, all pre-trained models were trained with a learning rate of 0.001 and used the Adam optimizer with a momentum value of 0.999. The ReLU activation function was used in all layers to improve non-linearity, while the softmax function was employed in the output layer to enable multi-class classification. The suggested LCNet model was trained using certain hyperparameters, guaranteeing effective learning and performance. The comprehensive setup of these parameters is shown in Table 1.

Table 1

Different hyper-parameters selected in the proposed CNN model

Hyper-parameter	Description
Learning rate	0.0001
Batch size	32
Number of epochs	250
Dropout	0.3
Optimizer	Adam
Momentum	0.999
Activation function	ReLu

C. Performance Matrices:

The suggested model's performance was assessed using several measures, including accuracy, precision, recall, and F1 score. Where, assessing accuracy and recall is an essential component of machine learning model evaluation, since it quantifies the balance between false positives and false negatives. Precision quantifies the ratio of accurately predicted positive samples to the total expected positives, reflecting the model's dependability in positive classifications. Conversely, recall measures the model's efficacy in identifying true positive samples inside the dataset. Furthermore, the F1 score, denoting the harmonic mean of accuracy and recall, was computed to provide a balanced assessment of model efficacy. An elevated F1 score indicates that the model achieves an effective equilibrium between accuracy and recall, making it a reliable instrument for classification endeavors.

These assessment measures guarantee that the proposed model accurately and reliably differentiates across various classes.

$$Accuracy = \frac{(TP+TN)}{(TP+TN+FP+FN)} \quad (1)$$

$$Precision = \frac{TP}{(TP+FP)} \quad (2)$$

$$Recall = \frac{TP}{(TP+FN)} \quad (3)$$

$$F1-Score = 2 \times \frac{(TP \times FP)}{(TP+FP)} \quad (4)$$

where: TP is True Positive, TN is True Negative, FP is False Positive, FN is False Negative

D. Hardware and Software Used:

This section presents and examines the outcome of the suggested strategy. The Keras library was employed in this study to create the suggested approach's structure. The Python-based Keras library provides a high-level API for creating deep learning architectures that can be built on top of other numerical computing libraries like TensorFlow. The proposed CNN model was trained with NVIDIA DGX A100 machine. The specification of the system is shown in Table 2:

Table 2

NVIDIA DGX A100 machine specification

Specification	Description
GPU	8xNVIDIA A100 Tensor core GPUs
GPU Memory	320 GB
Performance	5 peta FLOPS AI 10petaOPS INT8
CPU	Dual AMD Rome 7742, 128 cores, 2.25 GHz(base), 3.4 GHz(max boost)

RESULTS

This research assesses the efficacy of LCNet in identifying corn diseases, comparing its performance with three widely used pre-trained convolutional neural networks: MobileNetV2, ResNet50, and DenseNet201, as illustrated in Fig. 5-6 and Table 3, and compared with previous studies in Table 4. The assessment was grounded on critical performance criteria, including validation accuracy, validation loss, and computing efficiency, quantified by trainable and non-trainable parameters. All models were trained under identical parameter configurations, with a learning rate of 0.001, the Adam optimizer, and a momentum of 0.999, to provide an equitable comparison.

ResNet50 exhibited robust performance, with a validation accuracy of 91.27% and a validation loss of 0.2448. It necessitated 23,542,788 trainable parameters and 229,056 non-trainable parameters, making it computationally demanding. MobileNetV2 attained a validation accuracy of 90.19%, although recorded the greatest validation loss of 0.5175. It surpassed ResNet50 in efficiency, requiring 2,228,996 trainable parameters and 34,112 non-trainable parameters. DenseNet201 had the lowest validation accuracy at 87.88%, accompanied by a validation loss of 0.3413. Notwithstanding its reduced accuracy, it exhibited a markedly elevated computational burden, using 53,120 trainable parameters and 18,100,612 non-trainable parameters. The suggested LCNet model surpassed all pre-trained architectures, with the maximum validation accuracy of 94.65% and the lowest validation loss of 0.1559 as shown in Fig. 7. Moreover, LCNet exhibited exceptional computational efficiency, necessitating just 285,812 trainable parameters, making it an optimal selection for resource-limited settings.

The findings demonstrate that LCNet achieves an optimum equilibrium between precision and computing efficiency, making it suitable for real-time agricultural applications. The substantial decrease in trainable parameters indicates that LCNet can function efficiently on edge devices with constrained processing capabilities, hence guaranteeing its practical applicability for early disease detection in crops. The approach facilitates prompt disease detection, hence promoting proactive strategies to mitigate crop losses and enhance agricultural output.

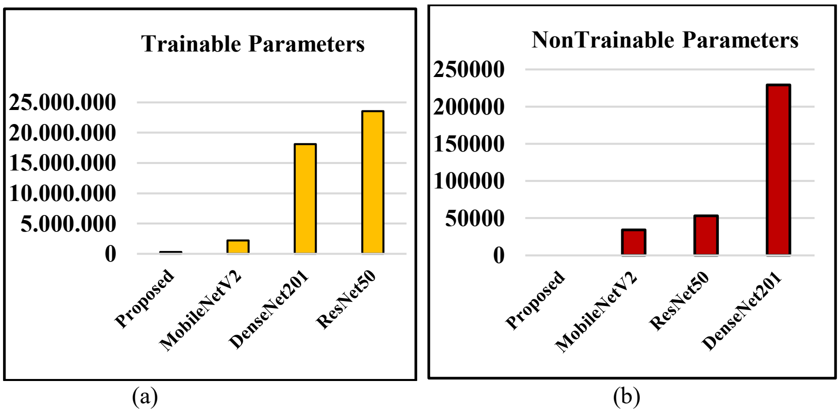


Fig. 5 - Comparison of total number of:
(a) trainable and (b) non-trainable parameters for proposed CNN, MobileNetV2, DenseNet201 and ResNet50.

Table 3

Performance of different models used in the study along with the proposed model

Model	Trainable Parameters	Non-trainable Parameters	Validation Accuracy	Validation Loss
MobileNetV2	2,22,89,96	34,112	90.19	0.5175
DenseNet201	1,81,00,612	53,120	87.88	0.3413
ResNet50	2,35,42,788	2,29,056	91.27	0.2448
Proposed Model	2,85,812	0	94.65	0.1559

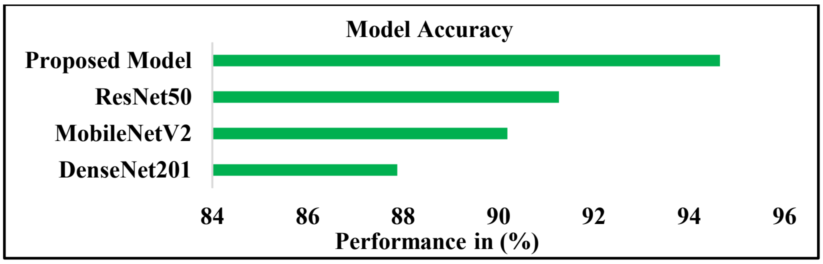
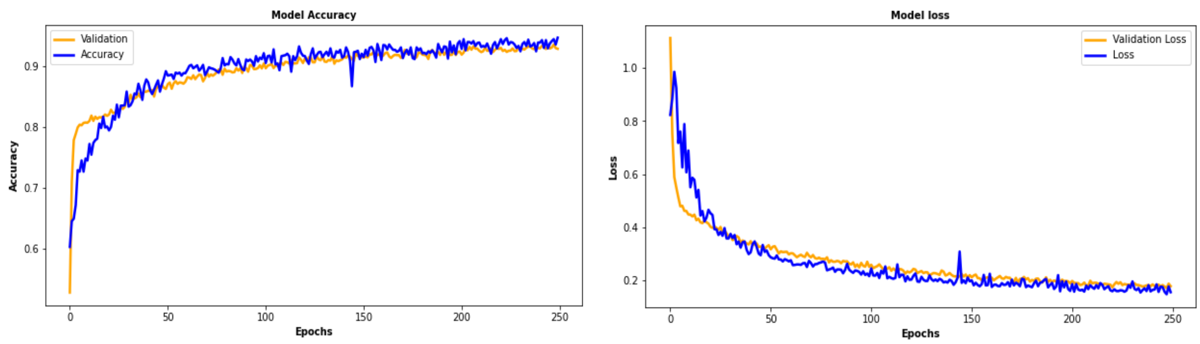


Fig. 6 - Performance of the proposed and pre-trained models in percentage (%)

Table 4

Performance comparison of the proposed model with past study based on corn

Study	Method	Accurcy (%)
Firmansyah et al., (2024)	Proposed CNN training from scratch	84.50
Hang et al., (2019)	CNN with inception module	91.70
Syarief et al., (2020)	AlexNet, VGG16-19, GoogleNet, Inception-V3, ResNet50-101	93.50
Proposed Model	LCNet	94.65



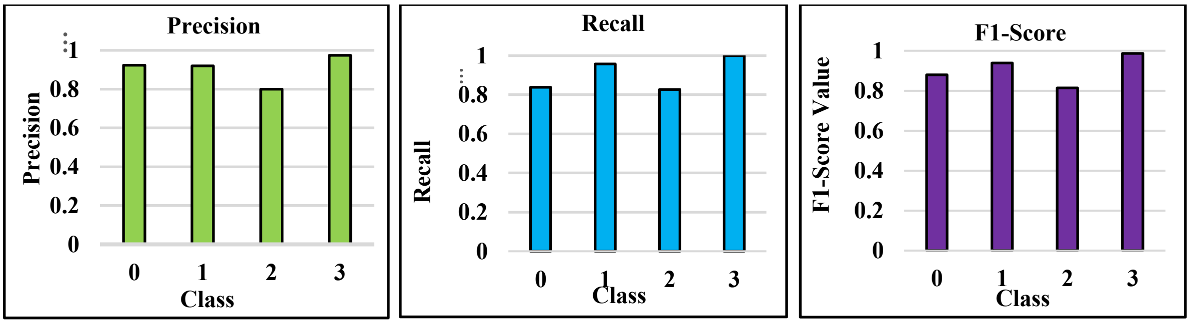
(a) (b)

Fig. 7 - (a) Accuracy and (b) Loss plot of the Proposed CNN Model

Table 5

Class-wise performance metrics—precision, recall and F1-score—achieved by the proposed model

Class Name	Class	Precision	Recall	F1-Score
Blight	0	0.9234	0.8391	0.8793
Common Rust	1	0.9194	0.9580	0.9383
Gray Leaf Spot	2	0.8000	0.8276	0.8136
Healthy	3	0.9749	1.0000	0.9873



(a) (b) (c)

Fig. 8 - Performance evaluation metrics

(a) Precision, (b) Recall and (c) F1-Score for the proposed model

CONCLUSIONS

This research presents an effective deep learning-based approach for classifying corn leaf diseases using a dataset of 4,188 images categorized into four groups: Common Rust, Gray Leaf Spot, Blight, and Healthy. A novel model, LCNet, was introduced and its performance was evaluated against established pre-trained architectures-MobileNetV2, DenseNet201, and ResNet50-as well as comparative studies from existing literature. LCNet demonstrated superior performance with a validation accuracy of 94.65% and a validation loss of 0.1559, outperforming MobileNetV2 (90.19%), DenseNet201 (87.88%), and ResNet50 (91.27%). These findings confirm LCNet's effectiveness in achieving high classification accuracy and efficient computation for corn leaf disease recognition. Looking ahead, future work will focus on fine-tuning model parameters through the Optuna optimization framework to further improve predictive accuracy. Additionally, the development of a lightweight mobile application is planned to support real-time, on-field disease detection, offering a practical and cost-effective tool for farmers and agricultural professionals.

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