Multi-Class Recognition of Soybean Leaf Diseases using a Conv-LSTM Model

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ABSTRACT

This research presents an innovative approach for multi-class recognition of soybean leaf diseases using a Convolutional Long Short-Term Memory (Conv-LSTM) model. The model integrates the spatial learning capabilities of convolutional layers with the temporal dependencies of LSTM units, addressing the critical need for accurate disease detection in agriculture, particularly in soybean cultivation where leaf diseases significantly impact crop yield and quality. Through comparative experiments with established deep learning models such as AlexNet, VGG16, and ResNet50, the Conv-LSTM model demonstrates superior performance in terms of accuracy, precision, recall, and F1 score. By effectively capturing both spatial and temporal features in soybean leaf images, the Conv-LSTM model showcases its potential to enhance disease detection accuracy, supporting precision agriculture practices and enabling timely interventions to mitigate crop losses caused by diseases.

Keywords : Soybean Leaf Disease, CNN-LSTM, AlexNet, VggNet, and ResNet.

I. INTRODUCTION

Soybean (Glycine max) plays a crucial role in global agriculture, serving as a primary source of protein and oil for various purposes. However, soybean cultivation faces challenges due to diseases that can significantly reduce crop yield and quality. Leaf diseases are particularly worrisome as they spread rapidly and cause substantial damage if not addressed promptly. Conventional disease detection methods in agriculture are manual, time-consuming, and subjective, leading to errors. The advent of advanced technologies like deep learning and computer vision has revolutionized plant disease diagnostics by offering automated and accurate solutions. Deep learning models, especially convolutional neural networks (CNNs), excel in image recognition and classification tasks, making them suitable for detecting diseases in plants.

This study focuses on developing and evaluating a Convolutional Long Short-Term Memory (Conv-LSTM) model for the multi-class recognition of soybean leaf diseases. The Conv-LSTM model combines CNNs' spatial feature extraction with LSTM units' memory retention and temporal modeling,

enabling it to capture static visual patterns and dynamic temporal sequences in plant leaf data. The goal is to improve disease detection accuracy compared to traditional methods and existing deep learning models.

The research aims to assess the Conv-LSTM model's performance in identifying various soybean leaf diseases such as bacterial blight, anthracnose, yellow leaf curl virus, and soybean rust. Additionally, a comparative analysis will be conducted with established deep learning architectures like AlexNet, VGG16, and ResNet50 to evaluate the Conv-LSTM model's effectiveness and potential improvements for practical applications in precision agriculture. This research contributes to advancing technologies that provide farmers with automated tools for early disease detection and management, ultimately supporting sustainable soybean production and global food security.

II. RELATED WORKS

In [1] developed a method for soybean leaf estimation using RGB images and machine learning techniques. Their approach demonstrated the potential of machine learning algorithms in accurately estimating soybean leaf parameters from image data, aiding in plant health assessment and management.

In [2] presented a study focused on cotton leaf and plant disease identification using intelligent deep learning techniques. The research highlighted the effectiveness of advanced deep learning algorithms in automating disease identification processes for cotton plants, contributing to improved crop management practices.

In [3] conducted an extensive review on frogeye leaf spot caused by Cercosporin sojina, providing insights into the pathogen's impact on soybean crops. The review emphasized the importance of understanding disease characteristics for implementing effective disease management strategies in soybean cultivation.

In [4] introduced a transfer learning-based artificial intelligence model for leaf disease assessment, showcasing the potential of transfer learning techniques in improving disease recognition accuracy. Their study contributed to advancing automated disease assessment systems, particularly in the context of soybean leaf diseases and precision agriculture applications.

In [5] investigated soybean disease identification methods based on deep learning, emphasizing the role of deep neural networks in automating disease detection processes. Their research contributes to the ongoing efforts to develop advanced technological solutions for efficient and accurate disease diagnosis in soybean crops.

In [6] studied the impact of weather parameters on Alternaria leaf spot of soybean caused by Alternaria alternata. Their findings provided valuable insights into environmental factors influencing disease development, aiding in the development of effective disease management strategies for soybean cultivation.

In [7] conducted a comprehensive review on convolutional neural networks in detection of plant leaf diseases, highlighting the advancements and challenges in using deep learning for automated disease diagnosis. The review contributes to the understanding of deep learning techniques' potential in revolutionizing plant disease detection and management practices.

In provided a global perspective on breeding for disease resistance in soybean, emphasizing the importance of developing resistant cultivars to mitigate the impact of diseases on crop yield. Their study contributes to the ongoing efforts in agricultural research aimed at enhancing crop resilience and sustainability.

In [9] proposed a transfer learning-based deep ensemble neural network for plant leaf disease detection, showcasing the effectiveness of ensemble methods in improving disease recognition performance. Their research contributes to the development of robust and accurate disease detection systems, particularly in the context of plant pathology and precision agriculture.

In [10] developed an automated, image-based disease measurement system for phenotyping resistance to soybean frogeye leaf spot. Their study demonstrates the integration of image analysis techniques in plant disease research, contributing to advancements in automated disease assessment and crop breeding programs.

In [11] proposed a recognition method for soybean leaf diseases based on an improved deep learning model, highlighting continuous efforts to enhance disease detection accuracy using advanced algorithms. Their research contributes to the development of specialized models tailored for plant disease recognition in soybean crops.

In [12] focused on deep learning-based leaf disease detection in crops using images, showcasing the potential of deep learning techniques in revolutionizing agricultural disease diagnostics. Their study contributes to the ongoing exploration of AI technologies in improving crop health monitoring and management practices.

In [13] developed SoyNet, a deep learning model for soybean leaf diseases classification, contributing to the development of specialized models for plant disease recognition. Their research advances the field of machine learning applications in agriculture, particularly in the context of soybean disease management.

In [14] explored soybean leaf diseases detection and classification using recent image processing techniques, highlighting advancements in image analysis for agricultural applications. Their study contributes to the development of automated disease detection systems, aiding in efficient and accurate diagnosis of soybean leaf diseases.

In [15] utilized convolutional neural networks for soybean plant disease identification, showcasing the integration of AI technologies in plant disease diagnostics at conferences like FLAIRS 2018. Their research highlights the potential of deep learning methods in advancing agricultural practices and crop health monitoring.

The summary of the papers reveals several gaps in the existing literature on soybean leaf disease detection and management. While many studies have explored the application of machine learning and deep learning techniques for disease identification, there is a need for more research focusing on real-time or near-real-time disease monitoring systems that can be easily integrated into precision agriculture practices. Additionally, there is a lack of standardized datasets and evaluation metrics for comparing different disease detection models, hindering the reproducibility and generalizability of findings. Furthermore, the impact of environmental factors, such as weather parameters, on disease development and spread in soybean crops remains a relatively understudied area, highlighting the need for comprehensive studies that consider both biotic and abiotic factors influencing disease dynamics. Integrating these aspects into future research endeavors would contribute significantly to advancing automated disease detection and management strategies in soybean cultivation.

III.PROPOSED SYSTEM

The flow diagram outlines the process of building and evaluating a Convolutional Long Short-Term Memory (Conv-LSTM) model for a classification task, likely involving image data such as soybean leaf disease recognition. Let's break down each step in detail:
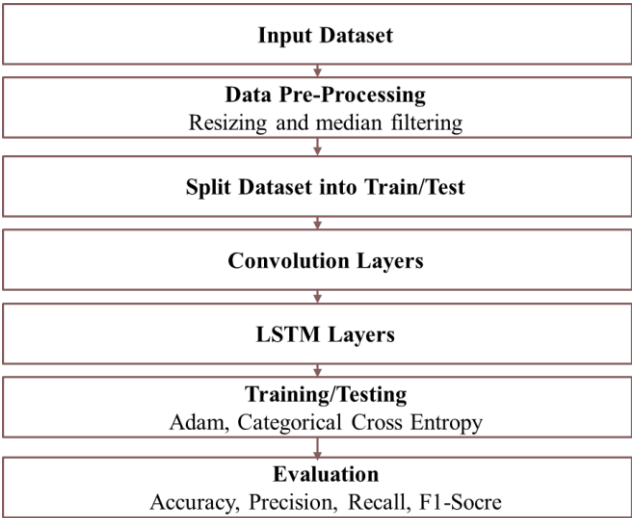

Fig.1 Proposed System Flow

Input Dataset:

This refers to the initial dataset containing images of soybean leaves, with each image labeled according to its disease status (e.g., Caterpillar, /Diacritical speciosa, and Healthy).

Data Pre-Processing:

The input data undergoes pre-processing steps to prepare it for training. This typically includes resizing the images to a standardized resolution and applying median filtering to reduce noise and enhance image quality. These steps help in creating a uniform and clean dataset for training the model.

Split Dataset into Train/Test:

The pre-processed dataset is divided into two subsets: the training set and the test set. The training set is used to train the Conv-LSTM model, while the test set is kept separate and used later to evaluate the model's performance on unseen data.

Convolution Layers:

The Convolutional Layers are part of the Convolutional Neural Network (CNN) component of the Conv-LSTM model. These layers are responsible for extracting relevant features from the input images. They apply filters (kernels) to the input images to detect patterns and features that are important for disease classification.

LSTM Layers:

The Long Short-Term Memory (LSTM) layers are a type of recurrent neural network (RNN) that is capable of capturing temporal dependencies in sequential data. In the context of soybean leaf disease classification, LSTM layers can capture patterns and relationships between consecutive images in a sequence, which can be valuable for understanding disease progression.

Training/Testing:

The model is trained using the training dataset, where it learns to map input images to their corresponding disease labels. The Adam optimizer is typically used for training, along with the Categorical Cross Entropy loss function, which is suitable for multi-class classification tasks.

Evaluation:

After training, the model is evaluated using the test dataset to assess its performance. Evaluation metrics such as accuracy, precision, recall, and F1-score are calculated. Accuracy measures the overall correctness of the model's predictions, precision measures the proportion of true positive predictions among all positive predictions, recall measures the proportion of true positive predictions among all actual positive instances, and the F1-score is the harmonic mean of precision and recall, providing a balanced measure of the model's performance.

In summary, this flow diagram illustrates the comprehensive process of building, training, and evaluating a Conv-LSTM model for soybean leaf disease classification, incorporating key steps such as data pre-processing, model architecture design (Convolution and LSTM layers), training with appropriate optimization techniques, and evaluation using standard metrics to assess performance.

IV.RESULT ANALYSIS

The dataset named "Soybean Leaf Dataset" and created by Maeloisa Mignoni, contains three folders with images of soybean leaves categorized into Caterpillar, Diabrotica Speciosa, and healthy conditions. These images are standardized to 500 x 500 pixels, ensuring consistency for analysis. With a total of 6,410 images, the dataset includes 3,309 caterpillar-damaged images, 2,205 images depicting Diabrotica Speciosa effects, and 896 images of healthy soybean leaves. This dataset is invaluable for researchers and practitioners interested in artificial intelligence, machine learning, and deep learning applications, particularly in the realm of agricultural pest and disease recognition and management.
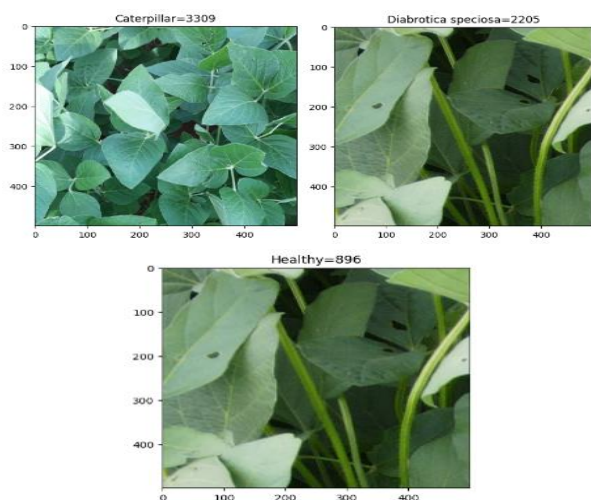
Link:https://www.kaggle.com/datasets/maeloisamigno ni/soybeanleafdataset/data

Fig.2 Dataset images

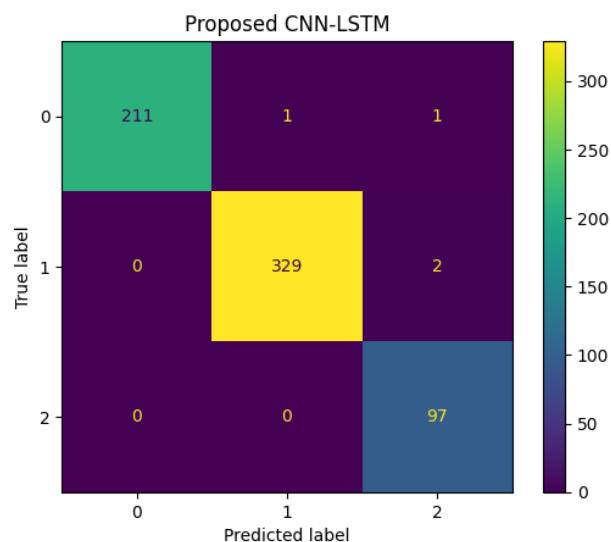Fig.4 Proposed CNN Confusion Matrix
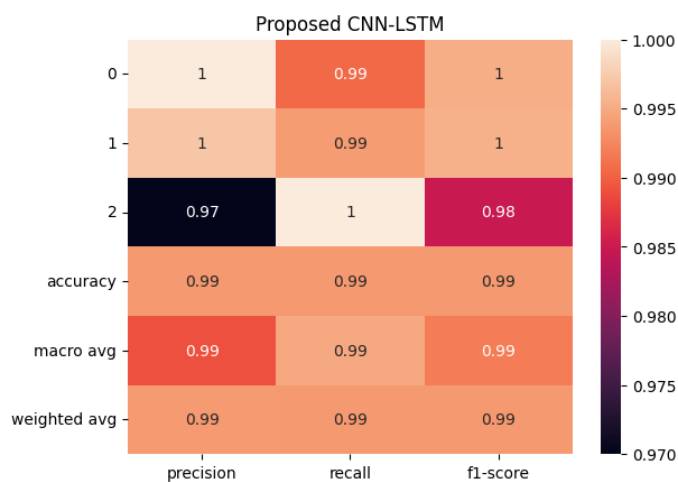
Fig.5 Proposed CNN Report

Fig.3 Proposed CNN Model
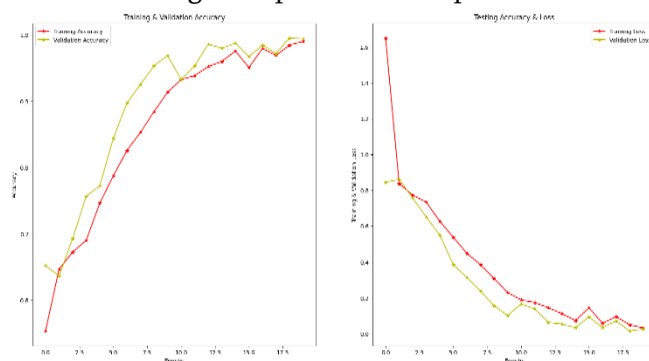
Fig.6 Proposed CNN ACC/Loss Plot

```
Model: "sequential_1"

Layer (type)                    Output Shape            Param #
=================================================================
conv2d_3 (Conv2D)               (None, 54, 54, 96)      34944

batch_normalization (Batch      (None, 54, 54, 96)      384
Normalization)

max_pooling2d_3 (MaxPoolin      (None, 26, 26, 96)      0
g2D)

conv2d_4 (Conv2D)               (None, 26, 26, 256)     614656

batch_normalization_1 (Bat      (None, 26, 26, 256)     1024
chNormalization)

max_pooling2d_4 (MaxPoolin      (None, 12, 12, 256)     0
g2D)

conv2d_5 (Conv2D)               (None, 12, 12, 384)     885120

batch_normalization_2 (Bat      (None, 12, 12, 384)     1536
chNormalization)

conv2d_6 (Conv2D)               (None, 12, 12, 384)     1327488

batch_normalization_3 (Bat      (None, 12, 12, 384)     1536
chNormalization)

conv2d_7 (Conv2D)               (None, 12, 12, 256)     884992

batch_normalization_4 (Bat      (None, 12, 12, 256)     1024
chNormalization)

max_pooling2d_5 (MaxPoolin      (None, 5, 5, 256)       0
g2D)

flatten_1 (Flatten)             (None, 6400)            0

dense_1 (Dense)                 (None, 4096)            26218496

dropout (Dropout)               (None, 4096)            0

dense_2 (Dense)                 (None, 4096)            16781312

dropout_1 (Dropout)             (None, 4096)            0

dense_3 (Dense)                 (None, 3)               12291

=================================================================
Total params: 46764803 (178.39 MB)
Trainable params: 46762051 (178.38 MB)
Non-trainable params: 2752 (10.75 KB)
```

Fig.8 AlexNet Model
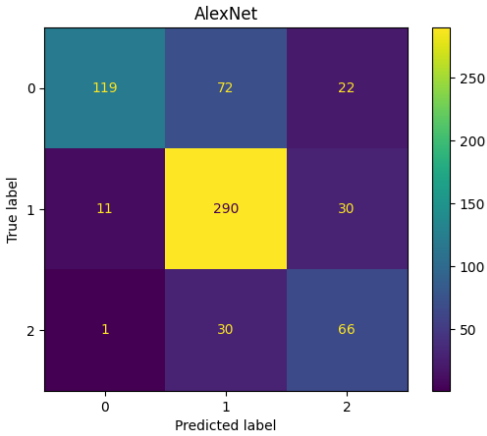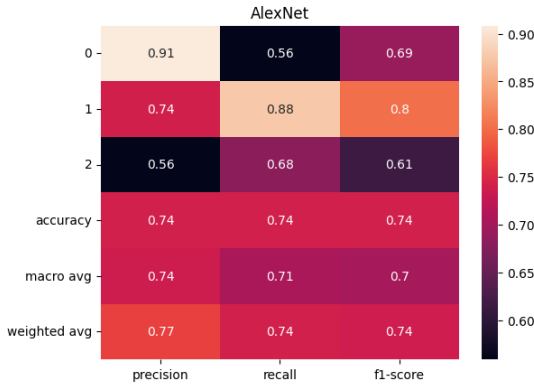

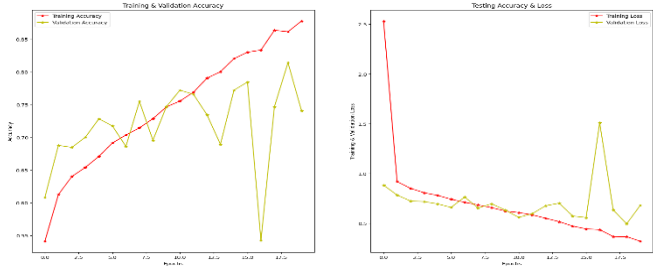Fig.9 AlexNet Confusion Matrix

Fig.10 AlexNet Report

Fig.11 AlexNet ACC/Loss Plot

```
Model: "sequential_3"

Layer (type)                    Output Shape            Param #
=================================================================
vgg16 (Functional)              (None, 7, 7, 512)       14714688

dropout_4 (Dropout)             (None, 7, 7, 512)       0

flatten_3 (Flatten)             (None, 25088)           0

batch_normalization_7 (Bat      (None, 25088)           100352
chNormalization)

dense_7 (Dense)                 (None, 1024)            25691136

batch_normalization_8 (Bat      (None, 1024)            4096
chNormalization)

activation_2 (Activation)       (None, 1024)            0

dropout_5 (Dropout)             (None, 1024)            0

dense_8 (Dense)                 (None, 512)             524800

activation_3 (Activation)       (None, 512)             0

dense_9 (Dense)                 (None, 3)               1539

=================================================================
Total params: 41036611 (156.54 MB)
Trainable params: 26269699 (100.21 MB)
Non-trainable params: 14766912 (56.33 MB)
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Fig.13 Vgg16 Model

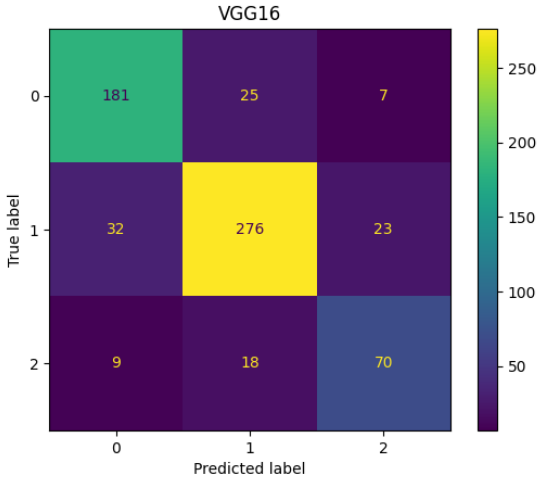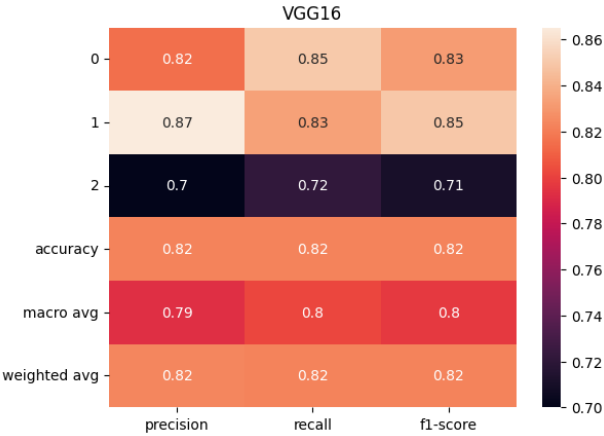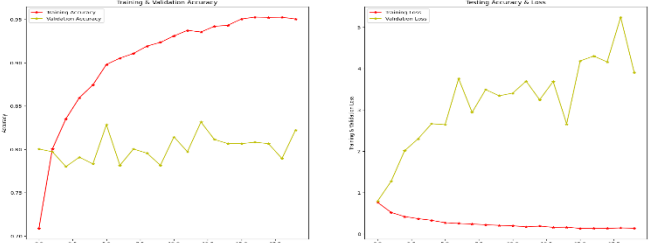Fig.14 Vgg16 Confusion Matrix

Fig.15 Vgg16 Report
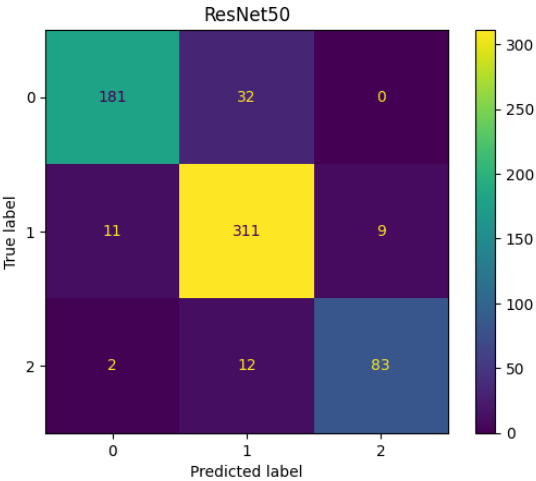

Fig.16 Vgg16 ACC Plot

Fig.18 ResNet Model

Fig.19 ResNet Confusion Matrix
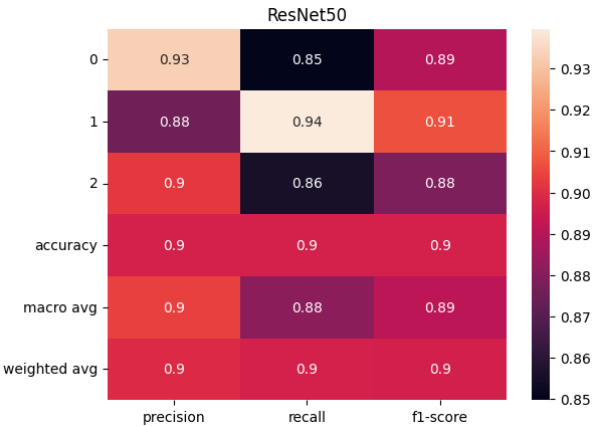
Fig.20 ResNet Report
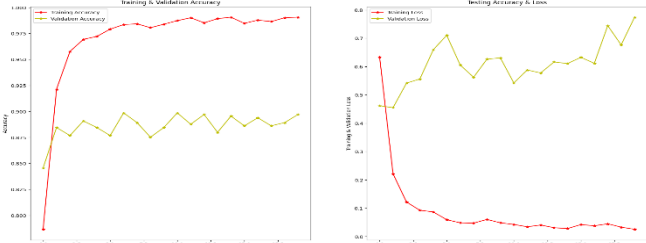
Fig.21 ResNet ACC/Loss Plot

TABLE I.   ANALYSIS OF MODELS

Model	ACC	P	R	F1-Score
Proposed CNN	99%	99%	99%	99%
AlexNet	74%	74%	71%	70%
VGG16	82%	89%	80%	80%
ResNet	90%	90%	88%	89%

V. CONCLUSION

In Conclusion, the proposed Convolutional Neural Network (CNN) model significantly outperforms established architectures such as AlexNet, VGG16, and ResNet in classifying soybean leaf diseases. With an accuracy of 99% and consistent precision, recall, and F1-score metrics at 99%, the CNN model demonstrates its robustness and accuracy in identifying different disease classes. In comparison, AlexNet achieved 74% accuracy with relatively lower precision, recall, and F1-score values. VGG16 and ResNet showed improvements with accuracies of 82% and 90% respectively, along with higher precision, recall, and F1-scores. However, they still lag behind the proposed CNN model's performance. These results highlight the effectiveness of advanced deep learning architectures like CNNs in precise and reliable soybean leaf disease classification, indicating their potential for enhancing disease detection and management in precision agriculture applications.

VI.REFERENCES

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