Detection of Corn Leaf Diseases Using Convolutional Neural Network and Transfer Learning

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***Abstract*—This study seeks to develop a neural network model for the identification of corn leaf diseases. Corn leaf diseases substantially affect agricultural yield and food security. Three different types of corn leaf diseases are caused by pathogens, and fungi drastically hamper production. Without proper action, the entire crop field can be infected, resulting in immense economic losses. By consuming affected crops, many diseases can enter the human body. This also increases the probability of getting cancer, which is fatal for humans. To address this issue, this study proposes a deep learning-based multiclass classification approach that leverages transfer learning (TL) and convolutional neural networks (CNNs) to identify various maize leaf diseases. A dataset of infected and healthy corn leaves is used to train the CNN model. This dataset has been gathered from Kaggle and other sources. Two supervised learning methods are used, and their performance is compared. A pre-trained DenseNet121 model is used for transfer learning to enhance the performance of our research. To identify leaves from four different classes, we employed softmax activation in our neural network's output layer. We achieved 93.4% accuracy with the convolutional neural network model and 98.21% accuracy with DenseNet121 during the evaluation phase. This model can be efficiently applied in our agricultural production. Compared with traditional methods, this process requires less time and offers an efficient way to detect corn or maize diseases.**

***Index Terms*— Agriculture, Classification, Computer vision, Convolutional neural network, Deep learning, Disease Detection, Transfer learning.**

I. INTRODUCTION

The economy of Bangladesh is mainly dependent on agriculture. As a developing country, basic food needs must be met. An essential crop in Bangladesh, corn (Zea mays) is fundamental to the nation's agricultural industry and food security. It has a high content of vitamins, fiber, and antioxidants. This is beneficial for eye health. Corn soup is widely used in patients' diets for its nutritional level. However, various fungal, bacterial, and viral diseases affect these plants, leading to significant production losses. Commonly known corn diseases include Northern Blight, Common Rust, and Grey Leaf Spot. Manual examination is the foundation of traditional disease detection techniques, and it is labor-intensive, time-consuming, and frequently wrong. To address these challenges, deep learning-based techniques have emerged as a promising solution for automatic and precise disease identification [1]. This paper proposes a deep learning methodology that employs convolutional neural networks (CNNs) and transfer learning to classify several maize leaf diseases commonly found in Bangladesh. By leveraging pre-trained models such as DenseNet121, we enhance detection accuracy while reducing computational costs and training time. Local farmers can capture an image of their crop with a smartphone and evaluate the model's performance. This helps with early disease diagnosis and the improvement of crop management practices in Bangladesh.

Despite the rapidly growing importance of corn in Bangladesh, the timely and accurate detection of corn diseases remains a significant challenge. The traditional manual inspection method is often infeasible due to lack of training and human error. In addition, many smallholder farmers lack access to agricultural experts, leading to delayed disease management and substantial yield losses. To address these obstacles, the objective of this investigation is to develop an automated, deep learning-based system that employs transfer learning and a CNN to detect and classify multiple maize leaf diseases. The proposed solution will provide a scalable, efficient, and accessible tool for farmers and agricultural professionals.

The main contributions and novelties of this study are summarized as follows: We developed a comparative framework comprising both a custom CNN and a transfer-learning-based DenseNet121 model for multiclass classification of corn leaf diseases. Unlike many previous studies that focused on a single deep learning architecture, this research provides a detailed performance comparison between a lightweight CNN and a pre-trained DenseNet121 model on the same dataset. The study utilizes a curated dataset containing four classes of corn leaves (Blight, Common Rust, Gray Leaf Spot, and Healthy) and demonstrates that transfer learning significantly improves classification performance. Moreover, our transfer learning model outperforms most of the previous models. The proposed framework is designed with practical agricultural applications in mind, particularly for developing countries such as Bangladesh, where early disease diagnosis can help farmers reduce crop losses and improve productivity.

Compared with previous studies, our work emphasizes a comparative evaluation of conventional CNN and transfer learning approaches for corn disease classification and discusses the feasibility of deploying these models in real-world agricultural environments. This study therefore provides an effective and computationally efficient framework for automated corn leaf disease detection.

II. Related Work

Detection of corn leaf disease has been a significant focus in agricultural research due to its impact on crop production and food security. Typical disease detection techniques rely on manual visual inspection, which is often imprecise and ineffective, particularly in large-scale farming. Recent advances in computer vision (CV) and deep learning (DL), which offer automated, highly accurate classification methods, have enhanced the identification of plant diseases. Convolutional neural networks, or CNNs, have been shown in numerous studies to be successful in classifying plant diseases. Sharmin et al. (2025) [2] present various machine learning techniques, including random forest, CNN, Long Short-Term Memory (LSTM), and Multivariate Adaptive Regression Splines (MARS), for predicting lettuce yield in a hydroponic system. In another research, Sharmin et al. (2025) [3] used transfer learning model DenseNet-121, ResNet-50, VGG-16, VGG 19, and Inception-V4 to classify 11 common leaf diseases of 20 different crops and vegetables, such as rice, wheat, corn, tea, coffee, soybean, potato, tomato, carrot, black gram, pea, cassava, sugarcane, bottle gourd, pepper bell, brinjal, lettuce, cabbage, cauliflower, cucumber etc. In their custom dataset, they achieved 97.58% accuracy with the DenseNet-121 model. Uddin et al. (2025) [4] offer several deep learning models such as EfficientNetB0, VGG16, VGG19 and ResNet50 to distinguish 10 different eggplant leaf diseases. They used a custom dataset of 3116 high-quality images. They achieved the highest accuracy, 98.70%, with the EfficientNetB0 model. In another study, Uddin et al. (2025) [5] utilizes DERIENet, a combination of EfficientNetB0, InceptionV3 and ResNet50 to classify multiclass jute leaf diseases such as Cercospora Leaf Spot, Golden Mosaic Virus, and healthy leaves.

Mohanty et al. (2016) [6] applied deep learning techniques to identify 26 plant diseases using the PlantVillage dataset, achieving high classification accuracy. Similarly, Too et al. (2019) [7] compared multiple CNN architectures, including VGG16, ResNet, and InceptionV3, for plant disease detection and found that deep learning performs noticeably better than conventional machine learning. To identify corn leaf diseases, research has focused on categorizing prevalent diseases as Northern Leaf Blight, Common Rust, and Gray Leaf Spot. Ritu et al. (2023) [8] proposed a custom CNN and transfer learning (TL) based models VGG-16 and VGG-19 to classify tomato leaf diseases of 11 classes. They achieved the highest accuracy and recall of 95.00% among all the model.

Islam et al. (2022) [9] proposed a computer vision-based apple and leaf disease detection system. Different apple diseases such as Black Rot, Apple Scab, Cedar Apple Rust have been identified successfully through this method. They used Plant Village dataset and their model get high accuracy of 98.63%. In [10], the author used different SVM methods to detect different diseases of the maize leaves with an accuracy of 89.6%. Even while this process works well with both large and robust datasets, it is not the most accurate. In [11], they have proposed a CNN model to predict potato diseases from potato leaves. Their model has performed well, achieving 98.33% accuracy.

Billah et al. (2024) [12] used CNN model architecture in categorizing five major tomato diseases such as bacterial spot, early blight, late blight, leaf mold, tomato mosaic virus, and healthy tomato plant leaves achieving 99.0% classification accuracy. Chithambarathanu et al. (2025) [13] proposed a CNN based architecture for identifying sweet corn diseases such as common rust, northern corn leaf blight, and maize dwarf mosaic. They used total 4450 of different leaf images as their dataset. Their CNN model performs well, achieving 96.30% accuracy.

Besides CNN, transfer learning is a widely popular image data classification method used in research and development. The author in [14] introduces a deep CNN method that uses transfer learning to diagnose illness in tomato leaves. AlexNet, GoogLeNet, and ResNet are used in the study as CNN's core architectures. The base model with ResNet achieves 97.28% accuracy by using fully connected training layers, stochastic gradient descent (SGD), and a batch size of 16. Nosiba et al. (2024) [15] used various transfer learning model VGG16, VGG19 and ResNet50 and machine learning algorithms such as Random Forest, Naive Bayes, K-Nearest Neighbors (KNN) and Logistic Regression to classify lemon and orange diseases. The ResNet50 model achieved 95.0% accuracy for lemon and 99.6% accuracy for orange. Ikorasaki et al. (2018) [16] used the Bayesian Classifier method to identify different corn diseases (Blighted Leaf, Rot of stem, Rot of stem, etc.). Their method got about 90% accuracy.

In [17], the author used two different machine learning algorithms, Principal Component Analysis (PCA) and Support Vector Machine (SVM), for the identification of different common corn leaf diseases. In [18], the author applied AlexNet, a deep learning model, to detect three common rice leaf diseases (bacterial blight, brown spot and leaf smut). They used the ImageNet dataset from Kaggle [19]. This dataset contains a total of 120 rice leaf images of three different classes. Their model achieved 99.42% accuracy. Baurai et al. (2024) [20] explored the KNN method in classifying different plant leaf diseases. Sardogan et al. (2018) [21] used a CNN along with the Learning Vector Quantization (LVQ) algorithm for tomato-leaf disease detection. They used a dataset of 500 images of tomato leaves with four symptoms of disease. Yadav et al. (2016) [22] combined the support vector machine technique with k-means clustering to classify grape leaf diseases. They achieved an accuracy of 88.89% in this method. Despite these advancements, challenges such as dataset limitations, model generalization, and real-world deployment remain. Many of the current models are based on controlled datasets, which could not work well in a variety of field settings with different lighting, angles, and background noise. Addressing these challenges through data augmentation, domain adaptation, and real-time mobile applications is crucial for practical implementation in regions like Bangladesh, where timely disease detection can significantly enhance agricultural productivity. Specifically designed for the Bangladeshi agricultural ecology, this work expands on earlier research using CNN-based multiclass classification with transfer learning to increase the precision and effectiveness of maize leaf disease detection.

III. Dataset Descriptions

The dataset used in this study was collected from publicly available datasets hosted on Kaggle, primarily the PlantVillage and PlantDoc repositories. A total of 4,188 RGB images of corn leaves were selected. The images belong to four categories: Northern Leaf Blight, Common Rust, Gray Leaf Spot, and Healthy leaves. Here, three of them have been identified as infected leaves, and the final one is the category of healthy leaves. Table I shows the distribution of these images.

Table I
Statistics of our image dataset

Diseases Type	Number of images
Northern Leaf Blight	1146
Common rust	1306
Gray leaf spot	574
Healthy leaf	1162

The dataset is visualized in the following Figures: 1, 2, 3 and 4. We can see that the affected classes are common rust, blight and gray leaf spot. The main cause of corn blight disease is a devastating fungal infection caused by either *Exserohilum turcicum* (Northern Corn Leaf Blight) or *Helminthosporium maydis* (Southern Corn Leaf Blight).

Fig. 1. Samples of Northern Leaf Blight infected corn leaves.

It appears as lengthy, yellow-haloed, tan-to-brown lesions that frequently follow the veins of leaves, giving them a “scorched” look. Southern blight lesions are smaller (1–2 cm) with distinct reddish-brown borders, while Northern blight shows larger (5–15 cm), cigar-shaped gray-green spots that turn brown. The disease spreads by windborne spores and grows best in warm, humid environments. Inhibiting photosynthesis can result in significant yield losses. Figure 1 shows different corn leaves infected by bight diseases.

Fig. 2. Samples of Common Rust infected corn leaves.

Corn Common Rust is a common foliar disease that is triggered by the fungus *Puccinia sorghi*. It is characterized by small, round to elongated, powdery blisters that are orange to brown and develop on both leaf surfaces. These blisters explode to release spores, which gives the leaves a rusty look. With high humidity and cool to moderate temperatures (16–25°C), the disease frequently manifests in the middle of the season. While rarely devastating, severe infections can reduce photosynthesis and yield by 10–20%. Common Rust blisters are darker, scattered, and primarily form on the upper leaf surface. Figure 2 depicts common rust infected leaves.

Fig. 3. Samples of Gray Leaf Spot infected corn leaves.

However, maize Gray Leaf Spot (GLS), a serious foliar disease of corn, is caused by the fungus Cercospora zeaemaydis and is characterized by rectangular, tan-to-grey lesions with noticeable yellow halos that are surrounded by leaf veins. Figure 3 depicts an infected GLS corn leaf. These wounds initially appear as small, necrotic spots before expanding into larger, blocky patches, often leading to premature leaf death. GLS thrives in warm (25–30°C), humid conditions and spreads via windborne spores, with severe infections causing yield losses of up to 50% by impairing photosynthesis. Unlike rusts or blights, GLS wounds lack pustules and maintain sharp, angular edges due to vein confinement.

Fig. 4. Samples of healthy corn leaves.

These images are randomly collected from our dataset for visualization purpose. The images were selected based on the following criteria: (i) clear visibility of disease symptoms, (ii) sufficient image resolution, (iii) removal of duplicate and severely corrupted images, and (iv) balanced representation of healthy and diseased leaves. The dataset contains images captured under different illumination conditions, viewing angles, and backgrounds, making it reasonably representative of practical field conditions. To avoid sampling bias, the dataset was divided using stratified sampling, ensuring that each disease category maintained approximately the same proportion in the training, validation, and test sets.

IV. Research Methodology

The methodology for classifying these diseases involved a comprehensive deep learning approach, beginning with data acquisition and preparation. The "Corn or Maize Leaf Disease Dataset," which included images classified as Healthy, Common Rust, Gray Leaf Spot and Blight, was utilized.

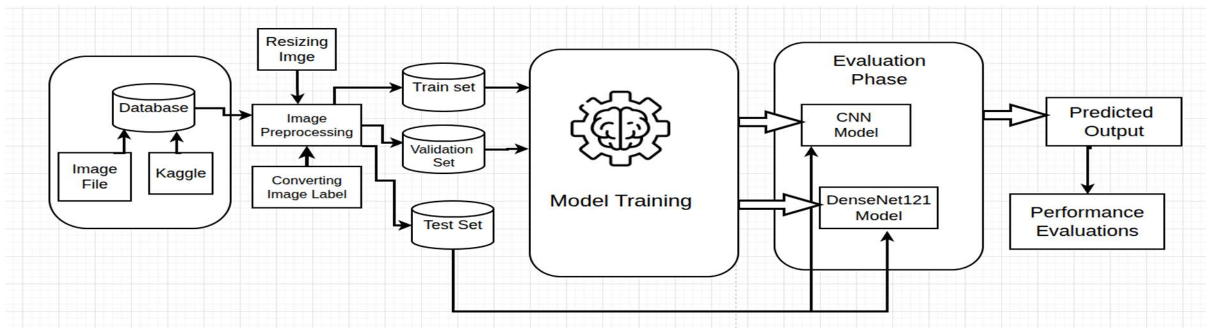

Fig. 5. Diagram of our proposed model workflow.

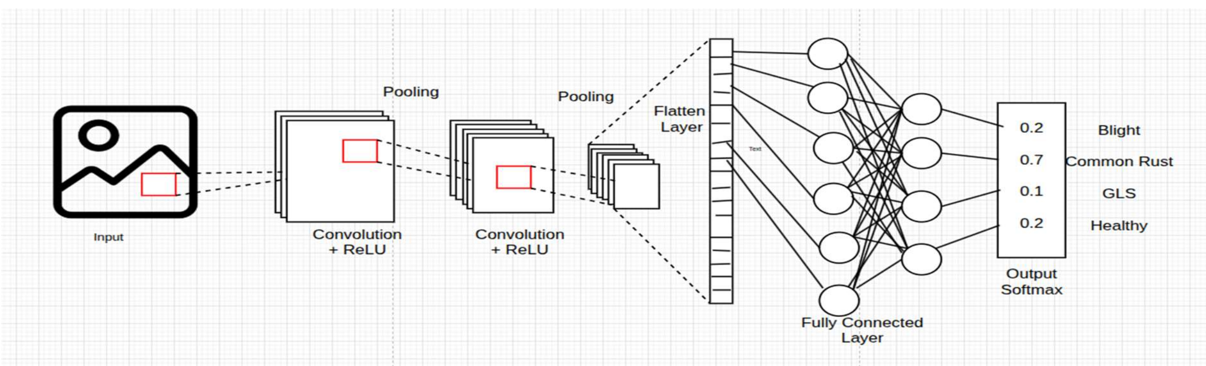

Fig. 6. The internal architecture of a convolutional neural network model. Here is a 2-layer neural network is shown.

Initially, the dataset was structured into a pandas DataFrame, mapping image file paths to their corresponding class labels. To ensure a robust evaluation, this dataset was partitioned using a stratified division into training (81%), validation (9.5%), and test (9.5%) sets, preserving the proportional representation of each class of disease in all subsets.

TensorFlow's ImageDataGenerator class was used to create an image data pipeline that methodically processed the photos by batch-organizing them, shrinking them to a consistent input size of 224x224 pixels, and transforming labels into a categorical format appropriate for model training. Two distinct modeling strategies were implemented and evaluated. The first strategy involved the construction of a custom Convolutional Neural Network (CNN) from the ground up. The second strategy is to apply the Transfer Learning (TL) method. After designing our model with appropriate layers, we trained our refined dataset on the distinct model through a few epochs. Each epoch needs to run forward propagation and back propagation to estimate our model parameters. After getting a satisfactory performance level, we evaluated our model with new test data and measured model accuracy. In Figure 5, we have demonstrated our research methodology.

A. CNN-Based Model

Our CNN model architecture is shown in Figure 6. In the CNN strategy, the model consists mainly of two types of layers. Conv2D layers, MaxPooling2D layers and a dropout method. In the convolution layer, a 2D filter is used. This filter is multiplied by the image pixels to obtain the final matrix.

The value of the filter determines which features are being selected. Figure 7 the working principle of the convolution layer. The image size is reduced by half in the MaxPooling2D layer after the Conv2D layer's output matrix has been passed through it. Each 2x2 matrix is replaced by the corresponding four pixels' peak value. This process helps reduce the image's dimensionality while preserving its overall characteristics. The final compressed feature image is then passed to the neural network.

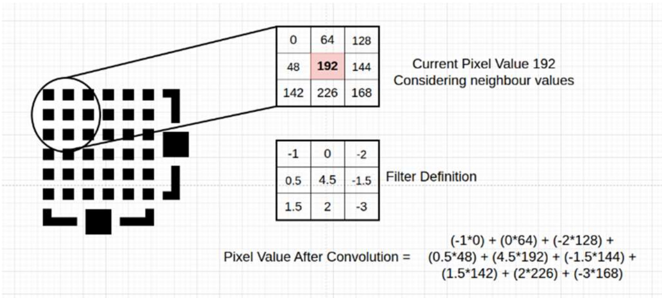

Fig. 7. Working mechanism of conv2d layer explained.

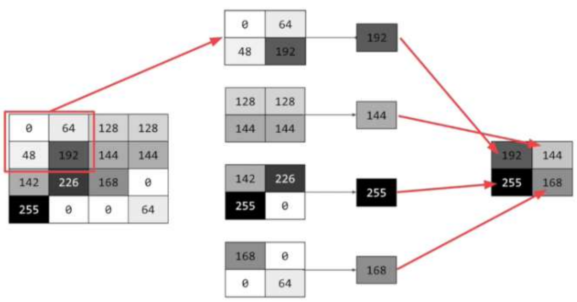

Fig. 8. The working mechanism of the maxpooling2d layer is explained.

In this network, there is one input layer and multiple hidden layers. In our case, the (224, 224, 3) shape image is compressed to a 4x4 feature matrix where 64 different filters are applied. This matrix is the input of our neural network. Each neuron signal (pixel value) of the input layer image matrix is multiplied by weights and bias. This result is passed through an activation function. In this case, we use the ReLU activation function, which sets negative inputs to zero.

$$ReLU(y) = \begin{cases} 0, & if\ y < 0 \\ y, & if\ y \geq 0 \end{cases} \quad (1)$$

The output of the first hidden layer is passed to the next hidden layer through a different set of weight matrix and bias terms. In the code, a dense layer is a fully connected layer in the neural network, specified by the number of neurons it contains. For multiclass classification, the output of the last hidden layer is run through the softmax algorithm [23]. This function estimates the probability that an image is healthy or infected. The softmax function's equation is provided below.

$$\sigma(x_j) = \frac{e^{x_j}}{\sum_{i=1}^{k} e^{x_i}} \quad (2)$$

The neural network (NN) prevents itself from overfitting by using the dropout technique. In this method, some randomly chosen neurons are ignored in the calculations.

B. Transfer Learning Based Model (DenseNet121)

We used the DenseNet121 model for transfer learning. It is a CNN-based model with 121 layers that have already been trained using the ImageNet dataset. This model is highly recommended for image datasets. To train our corn leaf data in this model, we create a separate data pipeline using tf.keras. Preprocessing. Image dataset from directory, which handles image loading, resizing to 256x256, and batching, with performance optimizations like caching and prefetching. An additional Dense layer with 256 neurons and an output layer with softmax activation were constructed on top of its 121 fixed layers. Again, we ran 40 training epochs on our data, achieving around 98.2% accuracy. This transfer learning model was trained exclusively on the custom head, allowing it to adapt its general image recognition knowledge to the specific task of identifying corn leaf disease. We used the held-out test data to thoroughly assess both models' performance. Creating comprehensive classification reports with metrics like precision, recall, and F1-score, viewing a confusion matrix to determine class-specific prediction accuracy, and examining training and validation accuracy and loss curves over epochs were all part of the evaluation.

V. Result Analysis

Since we are training our model in two different deep learning techniques, our results were measured in two different sections.

A. CNN model visualization

A 26-layer deep neural network framework was employed in our project. A number of convolution and max-pooling layers make up the primary layers. Since the images are 2D matrices, we select the conv2d layer, followed by the max_pooling2d layer. The convolution layer extracts different features from our images, whereas the max_pooling2d layer halves the image without compromising detail. The objective is to provide brief and straightforward visuals for the neural network. Batch normalization layers normalize our image to stabilize it. It also helps to achieve a higher learning rate. After the images have been reduced to the appropriate short format, they are passed through the flatten layer. Converts the 2D matrix to a 1D vector. This vector, which includes the general characteristics of the photos, is the input of our neural network model. To reduce the impact of overfitting, some neurons were then randomly removed using the dropout layer.

Since our model contains only one hidden layer, we employ a shallow neural network architecture. We choose 128 neurons in our hidden layer, which is connected to the input 1D vector image and the final layer. The layer that generates the output uses a softmax activation to determine the probability that an image belongs to a specific class [24]. The suggested class for the provided image has the highest likelihood.

This CNN model was initially fit on our image dataset for 100 epochs. Once the accuracy exceeds 98%, we employ a callback mechanism to end training. Our model took 36 epochs to reach 98%. The visual comparison between training & validation accuracy vs. the loss curve is shown in the following Figure 9. We can see that the highest accuracy in validation dataset is achieved in the 22nd epoch.

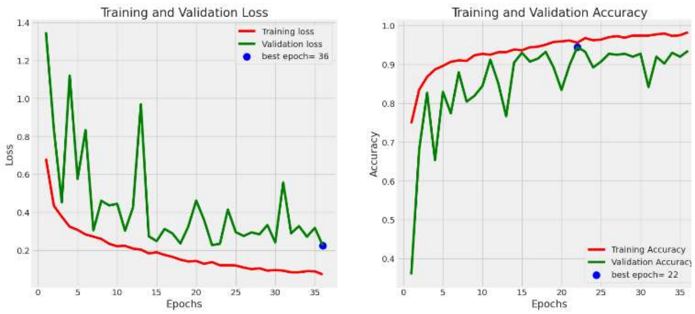

Fig. 9. The Accuracy vs. loss curve for our CNN model.

Table II
Classification report of our CNN model

	Precision	Recall	F1-score	Support
Blight	0.87	0.87	0.87	109
Common Rust	0.98	0.95	0.97	124
Gray Leaf Spot	0.74	0.78	0.76	54
Healthy	0.99	1.00	1.00	111
Accuracy			0.92	398
Macro avg	0.90	0.90	0.90	398
Weighted avg	0.92	0.92	0.92	398

Our model gradually increases accuracy and decreases loss as the training epochs continue. At last, we generate our CNN model's classification report. The following Table II describes the classification report of our CNN model. It describes the overall performance of our model. Then, a confusion matrix is produced that displays the performance of our test data. Here we can see that around 366 out of 398 images in the test set are predicted correctly.

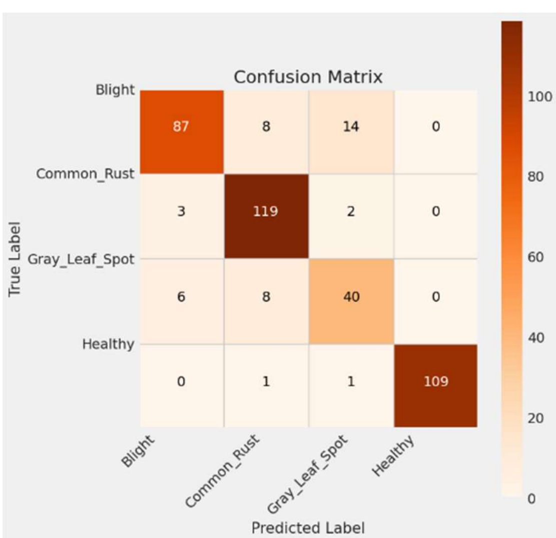

Fig. 10. The Confusion Matrix of our CNN model.

Now we can observe a random 16 images of predicted class vs. actual class. We can see that almost all the images are clearly predicted as actual in Figure 13.

B. *Transfer Learning DenseNet121 model visualization*

We run the same procedure on the transfer learning model, achieving 97.46% accuracy over 40 epochs on the training data. Figure 11 displays the model's accuracy and loss curves.

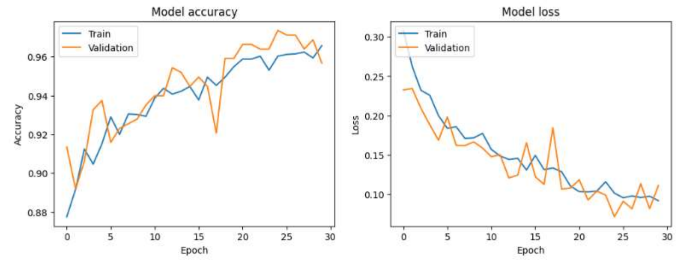

Fig. 11. Accuracy vs Loss curve of our Transfer Learning model

The classification report of our DenseNet121 model is given in Table III below.

Table III
Classification report of our DenseNet121 model

	Precision	Recall	F1-score	Support
Blight	0.96	0.99	0.98	126
Common Rust	1.00	0.99	1.00	141
Gray Leaf Spot	0.97	0.91	0.94	66
Healthy	0.99	1.00	1.00	115
Accuracy			0.98	448
Macro avg	0.98	0.97	0.98	448
Weighted avg	0.98	0.98	0.98	448

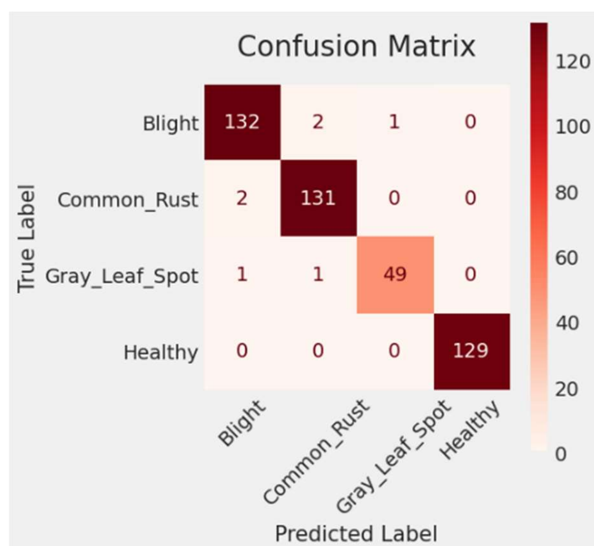

Fig. 12. The Confusion Matrix of our transfer learning (DenseNet121) model.

Our model's practical evaluation is shown in the following Figure. Since we have over 98% validation accuracy, we can see that almost all images have been sorted into the correct class, and our proposed model works just fine.

C. Performance Comparison

Our model's performance on the test data is shown in Table IV. Based on our evaluation, our transfer learning model outperforms the traditional CNN model. Figure 13 also provides evidence that the experiment with 16 test images yielded the expected result. After the model is trained on a set of images, its performance is evaluated on the test set, yielding satisfactory results.

Table IV
Model Performance Comparison on Test Data

Model Name	Accuracy (%)	Loss (%)
Convolutional Neural Network (CNN)	93.40	20.82
Transfer Learning (DenseNet121)	98.21	6.90

Fig. 13. Model practical evaluation result.

VI. Conclusion

The study successfully explored various aspects of deep learning (DL) by utilizing a Kaggle crop image dataset for the crucial task of corn leaf disease detection. Through a comparative analysis, the research demonstrated that while a basic Convolutional Neural Network (CNN) yielded promising results, the Transfer Learning (TL) approach, specifically employing the DenseNet121 model, significantly outperformed it in terms of accuracy and overall effectiveness. This robust model holds immense potential for practical application within the agricultural sector, offering farmers a powerful tool to accurately identify diseases in their valuable corn crops. By enabling early and precise diagnosis, the system empowers farmers to take timely and appropriate actions. Ultimately, this technological advancement represents a dynamic and efficient alternative to traditional, often unreliable, manual inspection methods, thereby enhancing food security and simplifying farmers' lives in an increasingly technology-dependent world. In future, we wish to work with more transfer learning models and create a mobile application so that it can be directly used in the crop field to detect infected crops by farmers with ease.

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