



Predictive Modeling of Maize Leaf Diseases Using Machine Learning Techniques

Amrita Kumari^{1*} • Nitesh Anand¹ • Ashish Saini¹ • Amit Kumar¹ • Sumit Sharma²

¹Department of Computer Science and Engineering, Quantum University, Roorkee, Uttarakhand, India

²Department of Computer Science and Engineering, Dev Bhoomi Uttarakhand University, Dehradun, 248007, Uttarakhand, India

*Corresponding Author's Email Id: amrita.cse@quantumeducation.in

Received: 24.02.2025; Revised: 27.12.2025; Accepted: 7.1.2026

©Society for Himalayan Action Research and Development

Abstract: Maize is one of the most significant crops used worldwide. Although significant monitoring and attention is paid on the proper growth of the plant throughout its cultivation cycle, various diseases, including leaf diseases, can affect the plant growth. This hampers the productivity of the corn plant. To minimize the crop loss, early detection and accurate diagnosis is very necessary. This also help prevent their spread. Deep Learning has been recently used in disease detection of various plants. Convolutional Neural Networks (CNNs) have demonstrated substantial potential in recent years for classifying images. In the present work, an approach based on CNN is proposed for predicting leaf diseases in corn plant. This method utilizes a trained EfficientNet baseline model by fine-tuning it on dataset of corn leaf images. Images of both healthy and diseased leaves, including those with early blight, common rust and late blight, are included in the dataset. New images of maize leaves are then classified into healthy or unhealthy categories using the trained model. This approach identifies maize leaf diseases such as Gray Leaf Spot, Leaf Blight and Common rust with an accuracy of 94.29%.

Keywords: Blight • Common rust • Convolutional Neural Networks • EfficientNet • Gray Leaf Spot.

Introduction

Maize being cultivated worldwide is one of the major cereal crops (Kaur et al 2020). Of the 170 nations that cultivate maize, India is ranked fourth in terms of production with the overall ranking of seventh. It makes up around respectively 2.4% and 4.6% of the total production and acreage of the world (Haque et al 2022).

Maize, during its life, is also affected by several leaf diseases which may hamper its productivity. Southern Corn Leaf Blight (SCLB) (also known as Maydis Leaf Blight (MLB)), Northern Corn Leaf Blight (NCLB) (also named Turcicum Leaf Blight (TLB)) and Banded Leaf and Sheath Blight (BLSB) are among the main illnesses that afflict most of India's maize-growing regions. NCLB is mostly dangerous and is a pervasive disease that affects maize leaves globally, particularly in India. *Exserohilum turcicum* is the fungus that causes NCLB, a fungal disease of corn or maize (Jackson-Ziems 2016). The fungus thrives in regions with high relative humidity

and moderate to cold temperatures where they are very active.

SCLB is a fungal disease that affects maize. The first indication is usually tan to brown lesions. Under the correct conditions, the lesions, which may resemble a normal rectangle, could combine to cause serious damage. It thrives in warm, humid climates (Haque et al 2021; Syarief and Setiawan 2020). If unchecked, it can drastically lower grain yield and quality.

Rhizoctonia solani is the pathogen that causes banded leaf and sheath blight which is primarily found in China, South and South East Asia. This disease can result in anything from minor crop losses to the complete eradication of crops. Furthermore, damaged leaves may lose their young tillers and dry up and perish more quickly. Common rust is also one of the disease responsible for reduction in crop yield but the impact is minimal. The infections caused by common rust are simple to identify and differentiate from other diseases (Syarief and Setiawan 2020; Sibiya



and Sumbwanyambe 2019; Mishra et al 2020). The harm caused by leaf diseases demands for prompt and precise diagnosis for increasing the output and lowering losses. Traditional disease detection techniques, which are normally used, frequently depend on manual observation, which could not be quick or accurate enough for large-scale farming operations. Furthermore, unskilled growers usually can't properly judge the disease, which results in inappropriate use of pesticides, which has a detrimental effect on maize quality, productivity and the environment. Recently, Deep Learning (DL) has proposed a potential solution to these issues. Deep learning models offer automatic diagnosis of leaf diseases which is highly accurate. This offers an efficient solution for detection of leaf diseases at the earliest. In particular, in image-related tasks, Convolutional Neural Networks (CNNs) have demonstrated amazing performance. This makes them an appropriate choice for interpreting the intricate visual patterns associated with various maize diseases. Such deep learning approach if effective, might significantly promote sustainability and enhance agricultural output overall (Panigrahi et al 2020). Considering the challenges, we have designed an EfficientNet-B0 model for the prediction of leaf diseases in corn.

Based on the literature survey, the diseases studied in this work include gray leaf spot (GLS), common rust (CR) and leaf blight (LB), which are most common in India. The main goal of the paper is to present EfficientNetB0 methodologies for categorizing different kinds of leaf diseases in corn (CR, GLS, and LB) and forecasting their severity.

Literature Survey

Numerous studies have been conducted to anticipate the diseases that would affect maize leaves. The majority of prediction methods have used deep learning, a subfield of machine learning (Amin et al 2022; Baliyan et al 2021). For diagnosing maize illness, Singh et al

(2024) proposed a new approach utilizing Random Forest Classifiers and CNNs. CNN was used to extract the features and then the classifier algorithm was utilized with Random Forest. Çakmak (2024) suggested using the EfficientNet deep learning network to classify leaf diseases in maize. The dataset initially contained 4188 images and was later enlarged to 6176 images. Leaf infections like gray spot, leaf blight, and common rust were examined. The performance parameters were obtained and compared using Dense-Net121, Inception V3, ResNet50 and VGG19 models. The maximum accuracy of 99.66% was obtained on the enhanced dataset using EfficientNet B3, whereas on the previous dataset, the EfficientNet B6 obtained 98.10% accuracy. In a different work, Rai and Pahuja Rai (2024) used a DL-based Attention U-Net model to examine a real-time approach for the segmentation and detection of NLB infections. In this work, after picture annotation, augmentation of data was done for increasing the effectiveness of the model. After training the model for maximum 50 epochs, utilizing Adam optimizer considering a learning rate of 0.0001 initially, the model performance on the test dataset was assessed. It was obtained that Attention U-Net model performed better than the Plain and Res U-Net image segmentation methods, with Intersection over Union (IoU) values of 70.91%, 72.41% and 51.95%. The model also attained an 85.23% average F1 score pixel by pixel.

Elmasry et al (2024) proposed a novel approach by integrating DenseNet121 with a classifier utilizing Deep Neural Network (DNN) for corn disease detection. This model, named DenseNetDNN, combines the feature extraction and classification capabilities of DenseNet121 and DNN respectively. The model performance was compared for various models: MobileNet, ResNet50, EfficientNetB0 and Xception were evaluated using precision, accuracy and recall.

In one such study, deep convolutional neural



networks were used to diagnose diseases in maize plants (Dash and Sethy 2024). The authors took 4,988 photos of the three different but frequent leaf diseases of corn: blight, common rust, and gray spot. All the images were tested and trained using 13 diverse pre-trained CNN models. Several performance parameters were used for the evaluation of the model. On comparison, the results depicted that highest False Positive Rate (FPR) was achieved by VGG-19 while Densenet201 has lower FPR.

Rashid et al (2024) developed a multi-model network with multi-contextual networks, which CNN techniques automatically exploit in a variety of forms. MMFNet incorporating fused features is far better than MMFNet without fused features in terms of accuracy. Because the training datasets were diverse, an overall accuracy of 99.23% was achievable. A new deep CNN model named TreeNet was proposed Malik (2024). It contained 35 layers and 38 connections. Dataset was obtained from Plant Village imaging for the training of the model. The image pre-processing was done by utilizing YCbCr color space, and Darknet-53 and DenseNet-201 along with TreeNet was utilized for feature extraction. For selecting the features, Entropy-coded Sine Cosine Algorithm was used. The model resulted in a classification accuracy, recall, F1-score and precision of 99.8%, 100%, 99%, and 99%, respectively.

The authors (Rachmad et al 2023) created a CNN-based classification system with four classes—healthy, common rust, blight, and

Implementation

GLS—utilizing a set of images of maize leaves. The images were taken from Madura Region's farmers' fields. Testing was conducted using a number of CNN architectural models. Five epochs with 100 iterations were used along with a learning rate of 0.0001. The data was distributed in a ratio of 7:3. This signifies train to test ratio. The test results for classifying corn pictures utilizing CNN with ResNet-50 architecture has shown an accuracy of 95.59%.

For the corn leaf disease detection, a hybrid model was provided by Ashwini and Sellam (2024). KaraAgro AI and Maize_in_field were the two datasets used. The simulation's findings indicate that the hybrid model has a performance level above 90% in predicting distinct classes of maize leaves on both datasets.

Olayiwola and Adejoju (2023) classified three commonly occurring diseases of corn leaves—LB, leaf spot and CR—using a CNN-based deep learning model named Keras on TensorFlow. The accuracy of accurately identifying each of the four classifications was 98.56%.

Dataset

A good dataset is required at every stage from training to evaluating the performance of algorithms. 4188 images in all have been collected from different sources. which are divided into four categories. One category is for healthy leaves, other categories include CR, LB, and GLS. Fig. 1 shows the maize leaf images with all the above mentioned illness along with the healthy leaf.

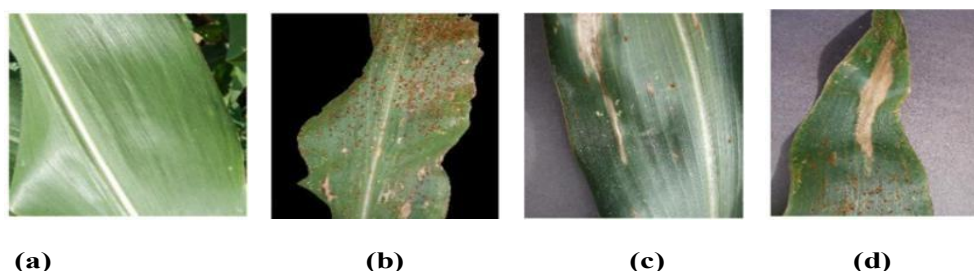


Fig. 1: Images of Maize leaf used in this work. (a) Healthy (b) Common Rust (c) Gray Leaf Spot (d) Blight.



A. EfficientNetB0

Algorithm:

Step 1: Data loading and preprocessing: This includes loading images and corresponding labels, splitting dataset into train, validate and test sets, applying data augmentation and normalizing images using EfficientNet preprocessing.

Step 2: Construct a model by loading EfficientNet-B0 as a base model with pre-trained weights. First 150 layers are frozen. Then, GlobalAveragePooling2D, Dense (512, ReLU), Dropout (0.5) and Dense (num_classes, Softmax) layer were added.

Step 3: The model is then compiled using the Adamax optimizer.

Step 4: Further, the model is trained using batch size of 32, with class weights for balancing. Then, early stopping is applied.

Step 5: The model is then evaluated on the test set and a classification report is obtained. Per-class accuracy is calculated from the confusion matrix. Next, training & validation loss/accuracy is plotted over epochs.

Step 6: The model performance trends, misclassification patterns and overfitting risks are then analysed.

Step 7: End.

The accuracy and loss have been calculated utilizing some standard formulas presented below:

$$\text{Accuracy} = \frac{T_p + T_n}{T_p + T_n + F_p + F_n}$$

(1)

$$\text{Recall} = \frac{T_p}{T_p + F_n}$$

(2)

$$\text{Precision} = \frac{T_p}{T_p + F_p}$$

(3)

$$\text{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

(4)

where T_p and T_n represents true positive and negative respectively and F_p and F_n represents false positive and negative respectively.

Results And Discussion

The development of deep learning methods has greatly enhanced image categorization, resulting in notable increase in efficiency and accuracy. The experiment was conducted using Kaggle Notebooks (Jupyter-based environment) with GPU acceleration and training the model for 30 epochs using the EfficientNet-B0 architecture, leveraging transfer learning. The evaluation metrics used include Precision, Recall, F1-score, Confusion Matrix and accuracy to assess model performance.

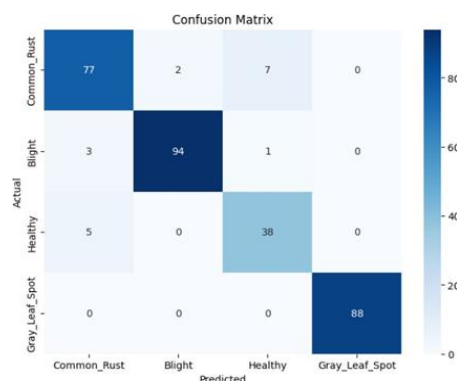


Fig. 2. Confusion Matrix for EfficientNet-B0 Model.



Table 1: Classification report of the proposed model.

	Precision rate	Recall	F1 score	Support
Healthy	1.00	1.00	1.00	88
Common rust	0.98	0.96	0.97	98
Grey Leaf Spot	0.83	0.88	0.85	43
Blight	0.91	0.90	0.90	86
Accuracy			0.94	315
Macro avg	0.93	0.93	0.93	315
Weighted avg	0.94	0.94	0.94	315

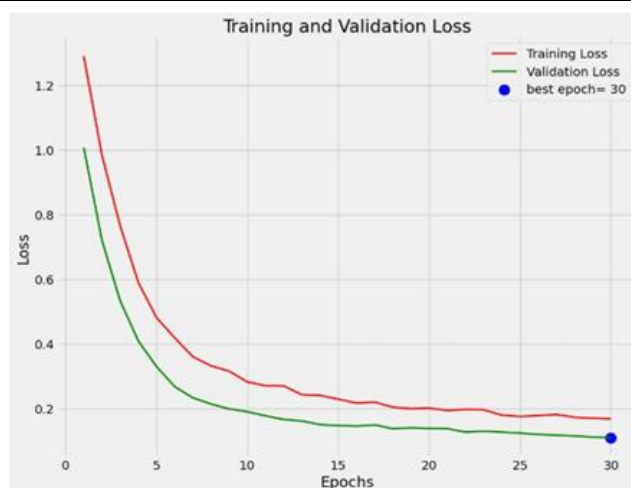


Fig. 3. EfficientNet-B0 model Loss Graph for Training and Validation data.

Table 1 shows the classification report of the proposed model. The model utilizing EfficientNet-B0 algorithm has a higher precision rate for Common Rust than for other diseases. The confusion matrix of the model is depicted in Fig. 2. Fig. 3 and 4 demonstrates

the loss and accuracy graph of the EfficientNet-B0 model.

The accuracy obtained for different classes shows the highest accuracy for detecting gray leaf Spot, which is 100%.

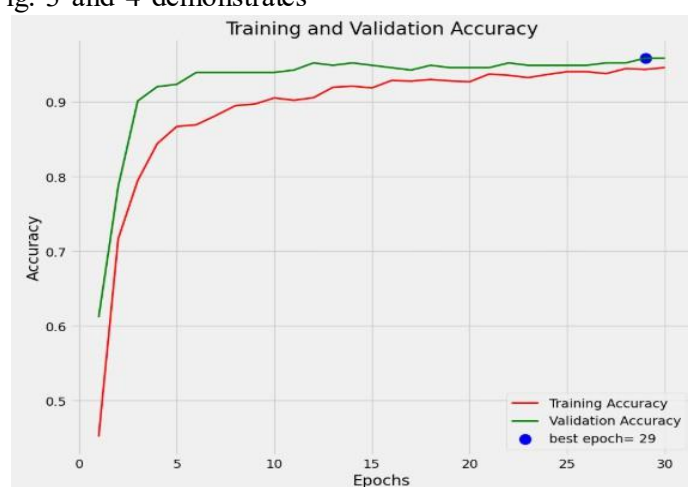


Fig. 4. Accuracy Graph for EfficientNetB0 model for Training and Validation data .

Conclusion: In light of maize's agricultural advantages and its role as a primary food

source, we have created an EfficientNet-B0 model to forecast prevalent illnesses in maize



plants. Common rust, blight, and grey leaf spot are among the diseases under investigation. This is required because illnesses reduce crop output, which in turn causes a food shortfall. Accuracy, F1 score, precision and loss are some of the parameters that have been used to calculate the model's performance. The model shows a fairly accurate result on the proposed model. Further, more advance EfficientNet models can be used to increase the accuracy.

Reference

- Amin H et al. (2022) End-to-end deep learning model for corn leaf disease classification. *IEEE Access*. 10: 31103-31115.
- Ashwini C and Sellam V (2024) An optimal model for identification and classification of com leaf disease using hybrid 3D-CNN and LSTM. *Biomedical Signal Processing and Control*. 92: 106089.
- Baliyan A et al. (2021) Detection of corn gray leaf spot severity levels using deep learning approach. In 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO). *IEEE*. pp. 1-5.
- Çakmak M (2024). Automatic Maize Leaf Disease Recognition Using Deep Learning. *Sakarya University Journal of Computer and Information Sciences*. 7(1): pp. 61-76.
- Dash A and Sethy PK (2024). Statistical analysis and comparison of deep convolutional neural network models for the identification and classification of maize leaf diseases. *Multimedia Tools and Applications*. 83(28): pp. 71189-71202.
- Elmasry A et al. (2024). A Novel Hybrid Approach Based on CNN for Corn Diseases Detection. *Optimization in Agriculture*. 1: pp. 94-104.
- Haque MA et al. (2021). Image-based identification of maydis leaf blight disease of maize (*Zea mays*) using deep learning. *Indian J. Agric. Sci*. 91(9): pp.1362-1369.
- Haque MA et al. (2022) Deep learning-based approach for identification of diseases of maize crop. *Scientific reports*. 12(1): p. 6334.
- Jackson-Ziems TA (2016) Northern Corn Leaf Blight. *Papers in Plant Pathology*. University of Nebraska-Lincoln. p. 550
- Kaur H et al. (2020) Leaf stripping: an alternative strategy to manage banded leaf and sheath blight of maize. *Indian Phytopathology*. 73: pp. 203-211.
- Malik MM (2024) A novel deep CNN model with entropy coded sine cosine for corn disease classification. *Journal of King Saud University-Computer and Information Sciences*. 36(7): p. 102126.
- Mishra S, Sachan R and Rajpal D (2020) Deep convolutional neural network based detection system for real-time corn plant disease recognition. *Procedia Computer Science*. 167: pp. 2003-2010.
- Olayiwola JO and Adejoju JA (2023) Maize (Com) leaf disease detection system using convolutional neural network (CNN). In *International Conference on Computational Science and Its Applications*. Cham: Springer Nature Switzerland. pp. 309-321.
- Panigrahi KP et al. (2020) Maize leaf disease detection and classification using machine learning algorithms. In *Progress in Computing, Analytics and Networking: Proceedings of ICCAN*. Springer Singapore. pp. 659-669.
- Rachmad A, Fuad M and Rochman EMS (2023) Convolutional Neural Network-Based Classification Model of Corn Leaf Disease. *Mathematical Modelling of Engineering Problems*. 10(2): pp. 530-536.
- Rai CK and Pahuja R (2024). Northern maize leaf blight disease detection and segmentation using deep convolutional neural networks. *Multimedia Tools and Applications*. 83(7): pp. 19415-19432.



- Rashid R, Aslam W and Aziz R (2024) An Early and Smart Detection of Corn Plant Leaf Diseases Using IoT and Deep Learning Multi-Models. IEEE Access. 12: pp. 23149-23162.
- Sibiya M and Sumbwanyambe M (2019) A computational procedure for the recognition and classification of maize leaf diseases out of healthy leaves using convolutional neural networks. AgriEngineering. 1(1): pp. 119-131.
- Singh E et al. (2024) Maize disease multi-classification: leveraging CNN and random forest for accurate diagnosis. In 2024 International Conference on Automation and Computation (AUTOCOM). IEEE. pp. 75-79.
- Syarief M and Setiawan W (2020) Convolutional neural network for maize leaf disease image classification. Telkomnika (Telecommunication Computing Electronics and Control). 18(3): pp. 1376-1381.