A Novel Approach Based on Convolutional Neural Networks for Maize Disease Detection

Authors: Kayombo Sakachiva, Jackson Phiri, Mayumbo Nyirenda

Abstract*—This study presents an improved method for detecting and classifying diseases in corn leaves using an enhanced ResNet-18 Convolutional Neural Network (CNN) model. To address the challenge of limited data and enhance the model's adaptability to real-world conditions, data augmentation techniques that simulate field environments are applied. The model is trained and tested on a curated dataset of maize leaf images, and its performance is evaluated using key metrics such as accuracy, precision, recall, and F1-score. The proposed approach achieves an excellent overall accuracy of 99.16%, significantly outperforming traditional CNN models. This demonstrates its strong performance and reliability, offering a scalable solution for automated plant disease detection, particularly in resource-constrained agricultural settings.

Keywords*—Corn Leaf Disease, Data Argumentation, Resnet 18, Convolution Neural Network (CNN)

INTRODUCTION

The agricultural sector is a fundamental cornerstone of the Zambian economic and social structure. The sector's influence extends wide, with some estimates indicating that agriculture plays a role in the livelihood of 8 out of 10 Zambians, either directly or indirectly. Agricultural production in Zambia consists of a range of activities, including crop production, livestock rearing, and fishery. Maize constitutes over 70% of the total output (Mt) among all primary crops. Agriculture remains a cornerstone of food security and economic growth in many regions, including Zambia. Corn (Zea mays), in particular, is a vital cereal crop. However, it is vulnerable to various foliar diseases like Maize Streak Virus (MSV), Northern Corn Leaf Blight (NCLB), and Gray Leaf Spot (GLS), which can drastically reduce yield.

Many CNN models don't perform well outside of controlled environments. Variations in lighting, cluttered backgrounds, and the different ways a disease presents itself at various stages can significantly affect model accuracy. A major reason for this is that most models are trained on uniform datasets that fail to reflect the complexity of real-world farming conditions [1].

To address these limitations, this study applies advanced data augmentation techniques to improve the robustness of the model. These techniques will artificially expand the training dataset by simulating real-world variations such as changes in lighting, different angles, and diverse leaf appearances. By exposing the model to these scenarios during training, it is expected to generalize more effectively and maintain high accuracy in unpredictable field environments.

RELATED WORKS

Researchers have explored various approaches for classifying and diagnosing plant diseases, including methods for extracting relevant features. In the agricultural field, deep learning, image processing, and traditional machine learning techniques have been widely applied. This section highlights previous studies that have utilized deep learning models to classify corn leaf diseases from digital images, aligning with the core focus of this research.

In [2], the authors suggested that recent access of smart devices can be utilized to provide automatic diagnosis of corn diseases and prevent severe crop losses. A real time method based on deep convolutional neural network for corn leaf disease recognition. Deep neural network performance is improved by tuning the hyper-parameters and adjusting the pooling combinations on a system with GPU. Further, the number of parameters of the developed model is optimized to make it suitable for real time inference. The pre-trained deep CNN model was deployed onto raspberry pi 3 using Intel Movidius Neural Compute Stick consisting dedicated CNN hardware blocks. During the recognition of corn leaf diseases, the deep learning model achieves an accuracy of 88.46% demonstrating the feasibility of this method.

In [3], the authors proposed a customized convolutional neural network (CNN) based Maize Plant Disease Identification model is presented along with various combinations of preprocessing techniques, namely Contrast Limiting Adaptive Histogram Equalization (CLAHE) on each RGB (Red, Green, and Blue) channel, log transformation, and

RGB to HSV (Hue, Saturation, and Variance) conversion of images. After preprocessing, these trained models were compared to the CNN and Support Vector-Machine (SV-M) models, trained without any preprocessing techniques.

In [4], the authors proposed a deep learning-based framework for pre-processing of dataset, automatic disease detection, severity prediction, and crop loss estimation. It uses the K-Means clustering algorithm for extracting the region of interest. Next, they employ the customized deep learning model 'MaizeNet' for disease detection, severity prediction, and crop loss estimation. The model reports the highest accuracy of 98.50%. Also, the authors perform the feature visualization using the Grad-CAM. Now, the proposed model is integrated with a web application to provide a user friendly interface.

Table1 highlights the main distinctive characteristics

for the reviewed work.

Reference	**Model**	**Key features**
[2]	Real-time Deep CNN with hyper parameter tuning	Hyper parameter tuning. Pooling adjustment. Real-time inference optimization.
[3]	Custom CNN + Preprocessing Techniques	CLAHE Log transformation. RGB to HSV conversion. Compared with SVM.
[4]	Deep Learning Framework + K-Means + MaizeNet	Preprocessing using K-Means. MaizeNet for detection & severity Crop-loss estimation Grad-CAM

Table 1

While previous studies have demonstrated promising results in maize leaf disease classification using CNN-based models, several limitations remain unaddressed. Some models, such as in [2], focused on real-time implementation and hyper parameter tuning but did not incorporate attention mechanisms or simulate real-world variability. Others, like in [3], relied heavily on manual pre-processing techniques such as CLAHE and RGB-to-HSV conversion, which may not generalize well across different environments.

Although [4] proposed a comprehensive pipeline involving K-Means clustering, severity prediction, and a web interface, it lacked strategies to enhance feature focus or generalization across different imaging conditions.

This study employs advanced data augmentation techniques to replicate real-world conditions, such as variations in lighting, background complexity, and different stages of disease development. By incorporating these simulated scenarios, the model is better equipped to generalize beyond controlled environments, offering reliable and practical support for smallholder farmers.

PROPOSED METHODOLOGY

In the proposed model, an image processing technique is employed to build a system capable of detecting leaf diseases quickly, even when supplied with low-quality or distorted images. This allows farmers, even those with limited knowledge of disease detection or modern digital tools, to use the system with ease. The input dataset comprises both healthy and diseased leaf images. Once the dataset is processed, the system generates an output that clearly distinguishes between healthy and affected leaves. The methodology is illustrated in the chart below.

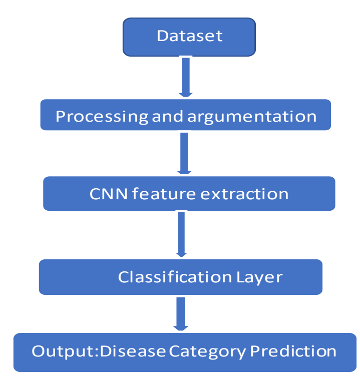

Figure 1

A. *Input Maize Leaf Image*

This stage begins with the acquisition or upload of a maize leaf image, usually captured using a

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smartphone or digital camera. The image acts as the initial input for the system and should display clear indications of either healthy or diseased conditions. Providing high-quality images at this point is essential to support reliable and accurate analysis in the subsequent phases.

$$I \in \{R\}^{\{H \times W \times C\}}$$

B. Preprocessing & Augmentation

Prior to model training or prediction, the input image is processed through steps like resizing, normalization, and noise reduction. Additionally, sophisticated data augmentation techniques are employed to replicate real-world variations such as shifts in lighting, orientation, scale, and background elements. This stage enhances the model's ability to generalize and perform reliably across diverse environments.

$$Iaug=P(I;h,w,\mu,\sigma,G\sigma,T)=T((\sigma resize(I,h,w)-\mu)*G\sigma)$$

CNN-Based Feature Extraction

A Convolutional Neural Network (CNN) is utilized to autonomously extract significant features from the preprocessed image. These features, which may include texture patterns, color distributions, and structural shapes, are essential for accurately distinguishing between healthy and diseased maize leaves. This process effectively converts the raw image data into a compact, high-level feature representation suitable for classification.

Output: Disease Category Prediction

In the final stage, the enhanced feature set is passed through a classification layer commonly utilizing a softmax function to generate a prediction of the disease category, such as healthy, blight, gray leaf spot or common lust. This output provides actionable insights for farmers and agricultural experts, enabling prompt decision-making and effective crop management.

IMAGE DATASET

The study utilized images from the maize-leaf-disease-dataset, which consists of 4,188 maize leaf samples. Each image features a single leaf and is classified into one of four categories: gray leaf spot (574 images), common rust (1,306 images), Blight (1,146 images), and healthy leaves (1,162 images). Representative examples from each category are shown in Fig. 2 to illustrate the dataset. The images displayed in fig. 2 were not subjected to any data augmentation techniques; hence, they appear in their original, unaltered form.

Table 2. Brief Description of the Dataset

S/N	DISEASE	NO OF DATASET
0	Blight	1,146
1	Common Rust	1,306
2	Gray Leaf Spot	574
3	Healthy	1,162
Total		**4,188**

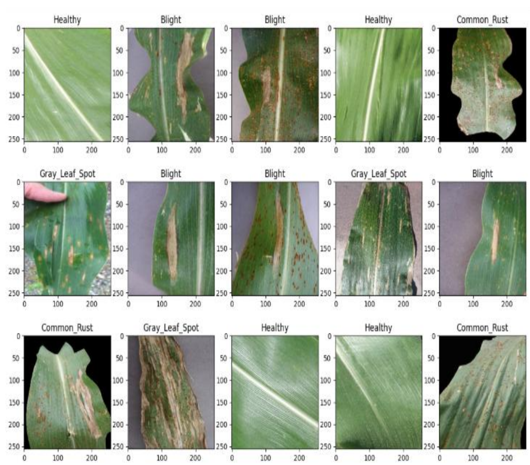

figure 2

C. Convolutional Neural Networks

Convolutional Neural Networks (CNNs) represent the state-of-the-art approach for image classification, as they are specifically designed to automatically learn and extract visual patterns from input images, passing the generated feature maps through successive deep layers for further analysis. In this study, we employed a CNN architecture called ResNet 18 to conduct our experiments.

D. Data Argumentation

Since data augmentation techniques are applied specifically to the training set, the resulting images often appear altered compared to the original dataset. These modifications may include blurring, as well as horizontal and vertical flipping, which increase variability and help the model generalize better during learning. Such augmentation strategies are widely recognized for reducing overfitting and improving CNN performance in image classification tasks.

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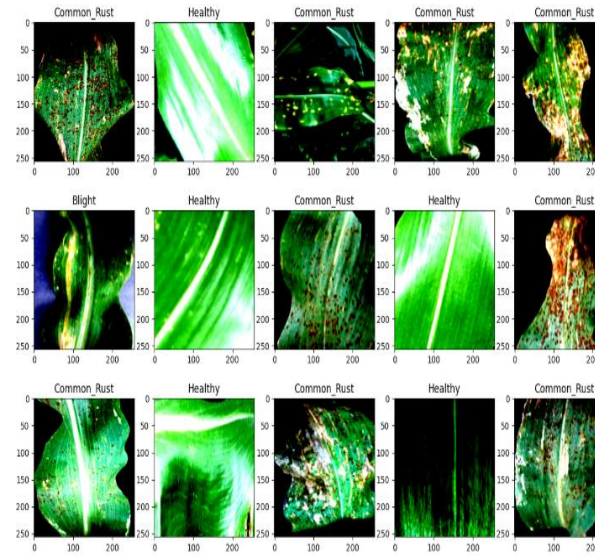


Figure 3

Prior to feeding data into a neural network, it should be organized into batches and shuffled to improve training efficiency and ensure randomness in sample presentation. However, since the test dataset is solely intended for evaluation and not involved in the training process, shuffling is unnecessary.

E. Evaluation Model

a) We built a maize disease detection system using a convolutional neural network based on ResNet. The network starts with a 7×7 convolutional layer followed by max-pooling to capture basic features from the images. It then goes through four residual layers, each made up of multiple BasicBlocks with skip connections. These skip connections help the network train deeper layers more effectively. As the data moves through the network, the number of feature channels gradually increases (from 64 to 512) while the image size is reduced. At the end, an adaptive average pooling layer condenses the features, and a fully connected layer produces predictions for four different maize disease categories. The residual connections improve gradient flow, allowing the network to classify complex images more accurately.

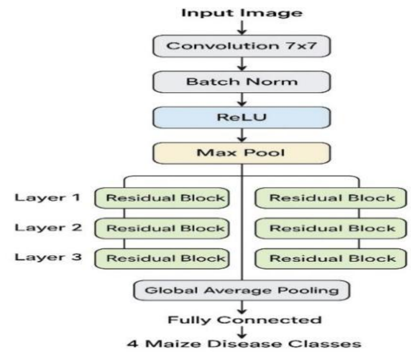


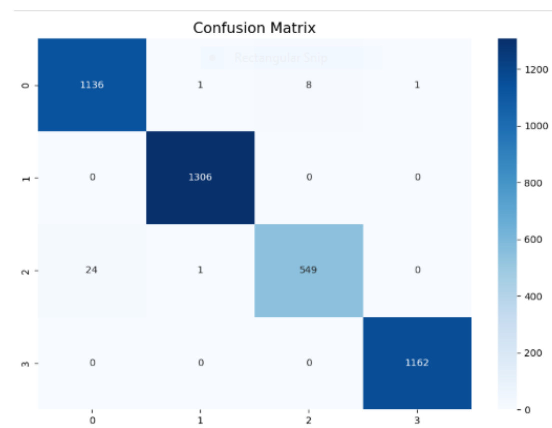
Figure 4

$$f(x) = \text{Softmax}\Big(W_{(fc)} \cdot GAP\left(ResBlocks\left(Conv7x7(x)\right)\right) + b_{(fc)}\Big)$$

The equation above means the model processes the input image by extracting features through convolutions and residual learning, summarizing them with global average pooling, transforming them with a final linear layer, and producing class probabilities using the Softmax function.

The figure below shows a confusion matrix, which is a tool used to evaluate the performance of a classification model. It compares the predicted labels (columns) against the actual labels (rows) for a set of data.

FIGURE 5. CONFUSION MATRIX



Key Observations

The diagonal values of the confusion matrix (1136, 1306, 549, 1162) indicate the number of instances correctly classified for each respective class. The off-diagonal values (such as 24, 1, 8) represent misclassified instances, where the model assigned an incorrect class label. Overall, the model demonstrates strong performance, as evidenced by the high counts along the diagonal, although certain misclassifications

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occur, particularly for class 0, where 24 instances were incorrectly predicted as class 1. To evaluate the performance of the model based on the confusion matrix, we calculated standard classification metrics, including accuracy, precision, recall (sensitivity), and F1-score for each class.

Class	**Precision**	**Recall**	**F1-Score**
0	0.9782	0.9913	0.9847
1	0.9985	0.9820	0.9902
2	0.9856	0.9964	0.9910
3	0.9991	1.0	0.9995
Overall Accuracy	99.16%		

Table 3

Training Progress

The image presents two plots depicting the training progress of a machine learning model over 14 epochs, showing the loss and accuracy for both the training and validation datasets.

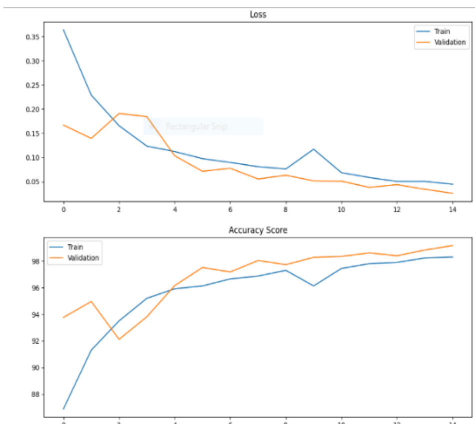

Figure 6

Top Plot – Loss: The X-axis represents the number of epochs (0 to 14), while the Y-axis shows the loss values (0 to 0.35).

Bottom Plot – Accuracy: The X-axis represents the number of epochs (0 to 14), while the Y-axis shows accuracy scores (88% to 99%).

CONCLUSION

In conclusion, the enhanced ResNet-18 CNN model demonstrates remarkable effectiveness in detecting and classifying maize leaf diseases, achieving an overall accuracy of 99.16%. By incorporating data augmentation to simulate real-world conditions, the model proves both adaptable and reliable. These results highlight its potential as a scalable solution for automated crop disease detection, particularly in supporting farmers within resource-constrained agricultural environments.

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