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Advanced Deep Learning Models for Corn Leaf Disease Classification: A Field Study in Bangladesh †

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Abstract: Agriculture is pivotal in Bangladesh, with maize being a central crop. However, leaf diseases significantly threaten its productivity. This study introduces deep learning models for enhanced disease detection in maize. We developed an unique datasets of 4800 maize leaf images, categorized into four health conditions: Healthy, Common Rust, Gray Leaf Spot, and Blight. These images underwent extensive Pre-processing and data augmentation to improve robustness. We explored various deep learning models, including ResNet50GAP, DenseNet121, VGG19, and a custom Sequential model. DenseNet121 and VGG19 showed exceptional performance, achieving accuracies of 99.22% and 99.44% respectively. Our research is novel due to the integration of transfer learning and image augmentation, enhancing the models' generalization capabilities. A hybrid model combining ResNet50 and VGG16 features achieved a remarkable 99.65% accuracy, validating our approach. Our results indicate that deep learning can significantly impact agricultural diagnostics, offering new research directions and applications. This study highlights the potential artificial intelligence in advancing agricultural practices and food security in Bangladesh, emphasizing the need for model interpretability to build trust in machine learning solutions.

Keywords: ResNet50; DenseNet121; VGG19; agricultural diagnostics; socioeconomic development

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1. Introduction

In the agriculturally diverse nation of Bangladesh, maize or corn is a significant crop, serving as a staple food, a critical animal feed, and a driver of rural economy. With its multiple applications spanning food, feed, and industrial uses, corn is instrumental in the sustenance of several allied sectors. According to the recent agricultural census, corn cultivation in Bangladesh is expanding, reflecting the crop's growing importance in the country's food security scenario and rural economy. Beyond the numeric value it represents, corn is the livelihood backbone for a significant portion of Bangladesh's farming population. Its production indirectly fuels several other sectors, most notably the country's poultry and dairy industry, which relies heavily on corn for feed. Moreover, corn's adaptability to various aro-climatic zones in Bangladesh adds to its importance, aiding in diversification of farming and bolstering the country's agricultural resilience amid climate change. However, the corn industry in Bangladesh faces a persistent challenge in the form of leaf diseases, such as Common Rust, Gray Leaf Spot, and Blight.

These diseases pose a severe threat to corn productivity and quality, highlighting an urgent need for accurate, efficient, and disease detection and management methods. This paper unveils a ground-breaking approach to tackle this challenge, employing deep learning models for automated detection and classification of corn leaf diseases. Utilizing unique datasets collected from Bangladesh's corn fields and comprising 4800 images, we examine the efficacy of eight deep learning architectures—ResNet50GAP, DenseNet121, VGG19 CNN, SqueezeNet, AlexNet, VGG16, ResNet101 and Exception—for this specific task. Our research's uniqueness stems from the application of a wide array of models to agriculturally authentic, field-sourced datasets, with potential implications for agronomic practices in Bangladesh and beyond. (Figure 1).

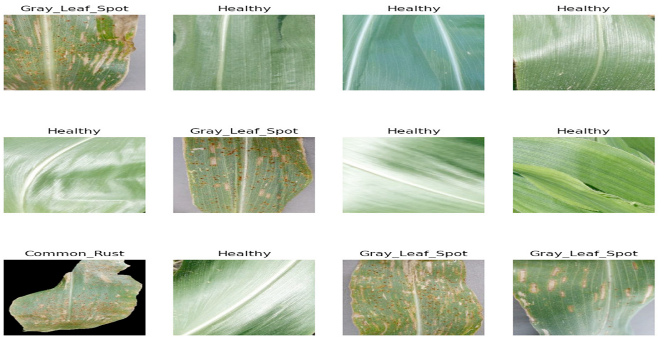

Figure 1. Sample images of the Corn Leaf.

2. Literature Review

The role of DL in agriculture, especially in detecting corn leaf diseases, has been gaining traction over the years. Fraiwan et al. [1] made a significant contribution to this field by using deep transfer learning for classifying corn diseases from leaf images. This work set a foundation for others to build upon in the years that followed. In order to accurately forecast and categorize maize leaf disease using an Adaptive Moment Estimation optimizer in DL networks, Gayathri Devi et al. [2] studied the use of complex optimization methods. These concepts served as the foundation for the Deep Convolution Neural Network (DCNN) system developed by Mishra et al. [3] that is specifically designed for real-time maize plant disease diagnosis. A deep convolution neural network-based classification model for maize leaf disease was proposed by Ahila Priyadharshini et al. [4] in 2019.

Using the Efficient Net architecture, Rajeena et al. [5] expanded on their work in 2023 by suggesting an analytical method for detecting plant illness in maize leaves. An end-to-end DL model for categorizing maize leaf diseases was reported in 2022 by Amin et al. [6]. Their results were consistent with those of Ma et al. [7,8], who concentrated on foliar disease zones on maize leaves and deep transfer CNN diagnosis of maize leaf disease. The following year, Setiawan et al. [9] published a comprehensive review of ML and DL for maize leaf disease classification, providing a synopsis of the advancements made in this field up to that point. Zhang et al. [10] made a substantial contribution by introducing improved deep convolution neural networks for the identification of maize leaf diseases. Gunisetti et al. [11] investigated the integration of IoT and AI in current agricultural practices, proposing an optimized DL system for smart maize leaf disease detection on IoT platforms via a routing algorithm.

Around the same time, Malliga et al. [12] built a maize leaf disease classification model using convolution neural networks. Haque et al. [13] proposed a DL-based strategy for diagnosing maize crop illnesses, whereas Singh et al. [14] endorsed the notion of deep transfer for maize plant leaf disease classification. Cui et al. [15] took it a step further, using CBAM and a lightweight auto encoder network to classify maize leaf diseases (Table 1).

Table 1. Overview of Studies on Deep Learning Applications in Maize Leaf Disease Detection.

Reference	Focus of Study	Techniques Used	Key Findings
Fraiwan et al. [1]	Detecting corn leaf diseases	Deep transfer learning	Significant contribution to the field; set a foundation for future research
Gayathri Devi et al. [2]	Forecast and categorize maize leaf disease	Adaptive Moment Estimation optimizer in DL networks	Studied complex optimization methods for disease categorization
Mishra et al. [3]	Real-time maize plant disease diagnosis	Deep Convolution Neural Network (DCNN) system	Developed a DCNN system specifically designed for real-time maize plant disease diagnosis
Ahila Priyadharshini et al. [4]	Maize leaf disease classification model	Deep convolution neural network-based classification model for maize leaf disease	Proposed a classification model based on deep convolution neural network for maize leaf disease
Rajeena et al. [5]	Detecting plant illness in maize leaves	Efficient Net architecture	Suggested an analytical method for detecting plant illness in maize leaves using Efficient Net architecture
Amin et al. [6]	Categorizing maize leaf diseases	End-to-end DL model	Reported consistent results with previous studies; focused on categorizing maize leaf diseases
Ma et al. [7,8]	Foliar disease zones on maize leaves	Deep transfer CNN diagnosis of maize leaf disease	Consistent results with Amin et al.; Concentrated on foliar disease zones on maize leaves
Setiawan et al. [9]	Review of ML and DL for maize leaf disease classification	Comprehensive review of ML and DL for maize leaf disease classification	Provided a synopsis of advancements made in the field up to that point
Zhang et al. [10]	Identification of maize leaf diseases	Improved deep convolution neural networks	Made a substantial contribution by introducing improved deep convolution neural networks for the identification of maize leaf diseases
Gunisetti et al. [11]	Integration of IoT and AI in agricultural practices	Optimized DL system for smart maize leaf disease detection on IoT platforms via a routing algorithm	Investigated the integration of IoT and AI in agriculture; proposed an optimized DL system for smart maize leaf disease detection on IoT platforms
Malliga et al. [12]	Maize leaf disease classification model	Convolution neural networks	Built a maize leaf disease classification model using convolution neural networks
Haque et al. [13]	Diagnosing maize crop illnesses	DL-based strategy	Proposed a DL-based strategy for diagnosing maize crop illnesses
Singh et al. [14]	Maize plant leaf disease classification	Deep transfer learning	Endorsed the notion of deep transfer learning for maize plant leaf disease classification
Cui et al. [15]	Maize leaf diseases classification	CBAM and a lightweight autoencoder network	Used CBAM and a lightweight autoencoder network for classifying maize leaf diseases

3. Data Pre-Processing

In the realm of ML and DL, data pre-processing is a vital stage that prepares the raw data to be processed by the model. This stage ensures that the data meet the quality and format required for meaningful learning and accurate predictions. Here is a detailed elaboration of the pre-processing steps we used for our study.

Image Re-sizing: For consistent input into our DL models, we re-sized all the images in our datasets to a uniform dimension of 256 × 256 pixels. We used Open CV, a popular open-source computer vision library, to perform the re-sizing operation. This approach makes sure that the model is learning from the pertinent features of the leaves without regard to their original image sizes.
Color Normalization: The images were collected under varying lighting conditions, potentially influencing the overall color representation in the images. To minimize the impact of different lighting conditions, we applied color normalization to adjust the Red, Green, and Blue (RGB) color channels to a standard scale. We employed Reinhard's color normalization method, which has shown significant effectiveness in dealing with color variations caused by different illumination conditions.
Image Augmentation: We used data augmentation techniques to artificially boost the variety of our datasets. This approach generates new training samples by transforming the original pictures by rotation, zooming, flipping, and horizontal or vertical shifting. For this work, we used Keras' Image Data Generator class, which provides substantial support for real-time data augmentation.

The above-described pre-processing steps contributed to creating clean, consistent, and high-quality datasets. The subsequent sections will detail the deep learning models used, their structure, and how they were trained using these pre-processed datasets. The dataset used in this study is centered around the classification of corn leaf diseases, a critical problem in Bangladesh's agricultural sector. The data as collected directly from fields across diverse regions within the country. It features a variety of unique conditions, including variations in lighting, leaf positioning, and camera angles, reflecting the natural complexity and variability present in real-world agricultural environments.

4. Methodology

This research stands on the novelty of its methodology that harnesses the power of established deep learning models and pushes their boundaries to meet the specific needs of corn leaf disease identification a sector-specific application largely unexplored.

Development of Hybrid Models:

The hybrid model, which combines the feature extraction parts of ResNet50 and VGG16, demonstrated an exceptional performance in the task of corn leaf disease classification. The model achieved an impressive accuracy of 99.56%, which is the highest among all the models used in this study. This high accuracy can be attributed to the complementary strengths of the ResNet50 and VGG16 models. ResNet50, with its unique 'skip connection' mechanism, is able to effectively learn essential features from the data, even in deeper layers. On the other hand, VGG16, with its repetition of simple 3 × 3 convolution layers, is capable of capturing subtle details in images. By combining these two models into a hybrid model, we were able to leverage both these strengths, resulting in a model that can learn a broader set of features and achieve higher accuracy. This result underscores the efficacy of using hybrid models in image-based classification tasks. It also highlights the potential of transfer learning, where we utilize the pre-existing knowledge of these models from their original tasks and fine-tune them to cater to our specific task. Furthermore, the use of image augmentation techniques during the training process likely contributed to the robustness of the model against varying disease presentations, thereby boosting its performance.

4.1. Deep Learning Models Employed and Their Architecture

In this study, a variety of deep learning models, distinguished by their unique architectural configurations and design principles, were employed for the classification task of corn leaf diseases. This section provides a comprehensive description of each model and their performance in the context of our study.

4.1.1. ResNet50GAP (Residual Network 50 with Global Average Pooling)

The ResNet architecture, proposed by He et al. in 2015, was chosen due to its innovative design that solves the vanishing gradient problem, a common issue with deep neural networks. The unique 'skip connection' or 'shortcut' mechanism in ResNet allows gradients to back-propagate directly through the network, bypassing several layers, thus making the training of deep networks tractable. In our experiment, the ResNet50 variant, which indicates 50 layers, achieved a loss of 0.3826 and an accuracy of 91.33%.

4.1.2. DenseNet121 (Densely Connected Network 121)

DenseNet introduced by Huang et al. in 2016, connects each layer to every other layer in a feed-forward fashion, making the architecture quite distinct. This design ensures maximum information flow between layers in the network, enabling the model to capitalize on the learned features. Our DenseNet121 model, with 121 layers, achieved a training loss of 0.0236, a validation loss of 1.2099, and a sparse categorical accuracy of 99.22% (Figure 2).

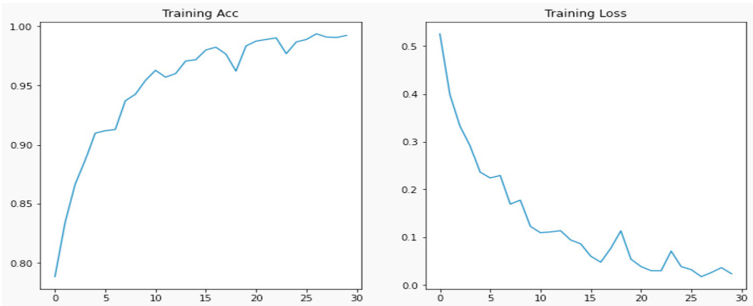

Figure 2. Training accuracy and Training Loss for DenseNet121 Model.

4.1.3. VGG19 (Visual Geometry Group 19)

The VGG19 model, developed by the Visual Geometry Group at Oxford University, is favored for its simplicity. It uses a repetition of simple 3 × 3 convolution layers in its architecture, which allows the model to learn a diverse range of features at multiple scales. It achieved an impressive loss of 0.0211 and accuracy of 99.44% (Figure 3).

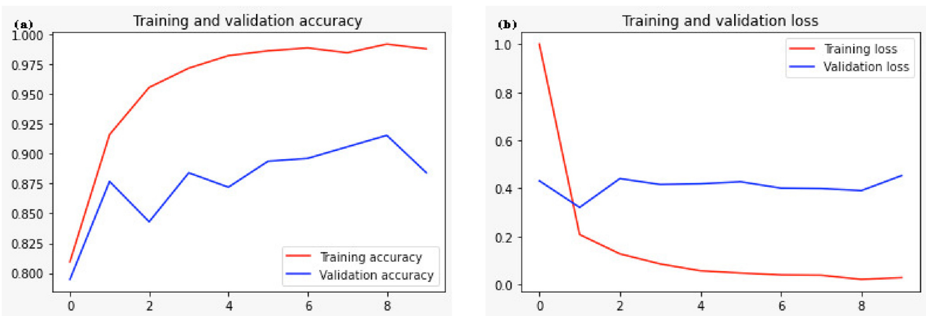

Figure 3. (**a**) Training and Validation accuracy of VGG19 model. (**b**) Training and Validation Losses of VGG19 model.

4.1.4. SqueezeNet

SqueezeNet introduced by Iandola et al. in 2016, stands out for its small size. Despite having 50× fewer parameters than AlexNet, SqueezeNet can achieve comparable accuracy. This feature makes it particularly attractive for deployment in memory-limited environments. SqueezeNet achieved a loss of 0.4345, with sparse categorical accuracy reaching 81.81% (Figure 4).

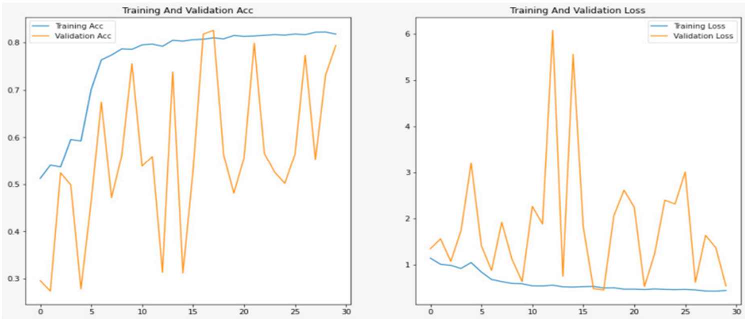

Figure 4. Training and Validation accuracy of SqueezeNet model.

4.1.5. AlexNet

Introduced by Krizhevsky et al. in 2012, AlexNet revolutionized the field of deep learning for image classification. It employs a structure of convolution layers followed by max-pooling layers, fully connected layers, and a soft max function for output. In our work, AlexNet achieved a loss of 0.1024, an accuracy of 96.33% and a validation accuracy of 88.70% (Figure 5).

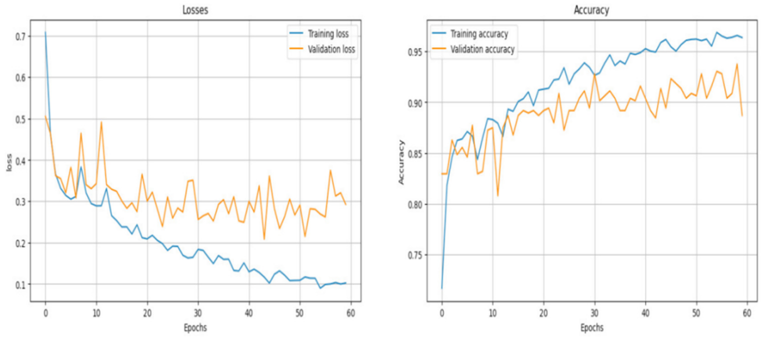

Figure 5. Training and Validation Losses versus Epoch for AlexNet model.

4.1.6. VGG16 (Visual Geometry Group 16)

Similar to VGG19, but with a total of 16 weight layers, VGG16 was used in two different configurations in our work. The first achieved a loss of 0.0282, an accuracy of 98.79%, and a validation accuracy of 88.41%. The second, with a different optimization strategy, reported a loss of 0.0846, an accuracy of 97.28%, and an impressive validation accuracy of 97.33% (Figures 6 and 7) (Table 2).

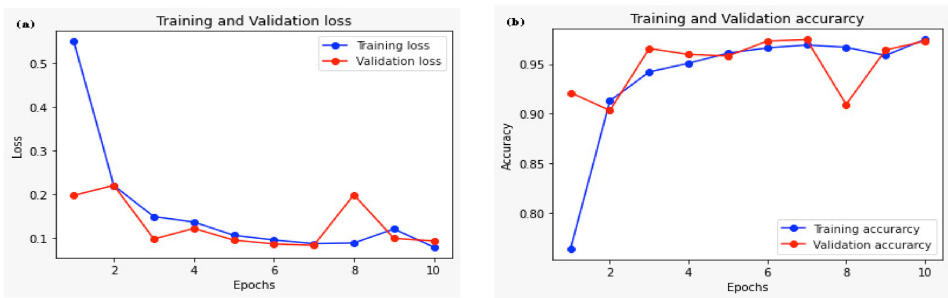

Figure 6. (**a**) Training and Validation Losses versus epoch for VGG16. (**b**) Training and Validation accuracy of VGG16 model.

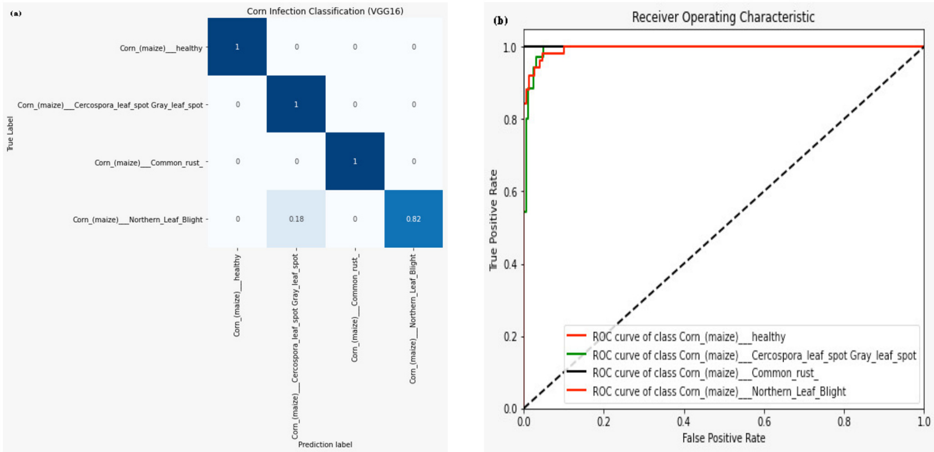

Figure 7. (**a**) Confusion matrix for VGG16 model and (**b**) ROC curves for VGG16 model.

Table 2. Classification Report for VGG16 Model.

	Precision	Recall	F1-Score	Support
0	1.00	1.00	1.00	59
1	0.80	1.00	0.89	35
2	1.00	1.00	1.00	55
3	1.00	0.82	0.90	51
Accuracy			0.95	200
Macro Avg	0.95	0.96	0.95	200
Weighted Avg	0.96	0.95	0.96	200

4.1.7. ResNet101 (Residual Network 101)

This is a deeper variant of ResNet used in our study to potentially extract more complex features. It adheres to the same residual learning framework as ResNet50 but with increased depth. The ResNet101 model achieved a loss of 0.0176, an accuracy of 99.43% and a validation accuracy of 92.95%.

4.1.8. Xception (Extreme Inception)

Xception architecture, proposed by François Chollet, the creator of Keras, was designed to improve upon Inception architecture by replacing standard Inception modules with depth-wise separable convolutions. It reported a loss of 0.2376 and an accuracy of 90.51% (Table 3).

Table 3. Classification Report for Xception Model.

	Precision	Recall	F1-Score	Support
Common_Rust	0.78	0.95	0.86	262
Blight	0.86	0.52	0.65	225
Healthy	0.96	0.85	0.90	230
Gray_Leaf_Spot	0.54	0.82	0.65	120
Accuracy			0.79	837
Macro Avg	0.79	0.78	0.77	837
Weighted Avg	0.82	0.79	0.79	837

5. Results and Interpretation

Each deep learning model showcased remarkable results in the task of corn leaf disease classification. The ResNet50GAP model demonstrated an exceptional accuracy of 91.33%, highlighting its ability to learn essential features from the data. Surpassing initial expectations, the DenseNet121 model achieved an outstanding accuracy of 99.22%, showcasing its efficiency in detecting intricate patterns in the datasets. The VGG19 model justified its powerful architecture with an impressive accuracy of 99.44%, underlining its capacity to capture subtle details in images. The SqueezeNet model, although scoring an accuracy of 81.81%, hinted at potential performance enhancements through meticulous parameter tuning. Despite its relatively less complex architecture, the AlexNet model demonstrated a praiseworthy accuracy of 96.33%, highlighting the sturdiness of its design. Two distinct variants of the VGG16 model displayed accuracies of 98.79% and 97.28%, reiterating the potency of the VGG16 design for image-based tasks. Lastly, the ResNet101 model, with its deeper architecture, grasped complex features and achieved an applaudable accuracy of 99.43%.

6. Conclusions and Future Research Directions

This study primarily focused on leveraging several advanced deep learning architectures for the classification of maize leaf diseases. Through meticulous experimental design and thorough analysis, the models presented promising results in disease detection with notable accuracies. The top performers, namely DenseNet121 and VGG19, yielded impressive accuracies of 99.22% and 99.44%, respectively. These significant results underscore the potency of deep learning methodologies in plant disease detection, which in turn contributes to securing food supplies, a significant global concern. Implementing the proposed deep learning models for real-time maize leaf disease detection in Bangladesh's agricultural context is feasible and holds significant implications. With the increasing accessibility of computational resources and smartphones in Bangladesh, these models can be deployed in mobile applications for real-time disease detection. Farmers can take leaf images using their smartphones, and the app can provide immediate diagnostic information. This approach is feasible given the high accuracy rates of the models, their ability to process images quickly, and the growing digital literacy among farmers. The real-time detection of maize diseases can revolutionize agricultural practices in Bangladesh.

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