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Classification of Corn Leaf Diseases Using Convolutional Neural Network

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Abstract: The study employs a deep learning model using Convolutional Neural Network (CNN), specifically the ResNet34 model, for detecting common corn leaf diseases in the municipality of Polomolok and General Santos City, Philippines. Corn, a vital staple crop and key economic commodity, is highly susceptible to diseases that threaten productivity and food security, making accurate and efficient detection crucial for effective management and yield optimization. The dataset used in the study comprises 27,146 images categorized into five classifications: Brown Spot, Corn Rust, Leaf Blight, Maize Streak Virus, and Healthy leaves. To improve model generalization and address class imbalance, data augmentation techniques of Basic Image Manipulation such as rotation, scaling, flipping, shearing, and color transformation were applied. The proposed model achieved an overall classification accuracy of 98.67%, with consistently high precision, recall, and F1-scores across all categories, as further validated through confusion matrix analysis that confirmed its strong performance in distinguishing between disease classes. To extend practical utility, an initial version of a mobile application called LeafScan was developed, which allows users to take or upload corn leaf images for disease prediction. These findings demonstrate the effectiveness of deep learning in agriculture, offering a reliable and scalable tool for disease classification and proactive crop management. The study provides a foundation for implementing AI-driven agricultural solutions in the Philippines. Future work could focus on developing a fully functional and user tested mobile expert system application for real-time disease detection and on expanding the model to include additional corn diseases for broader applicability in precision farming.

I. Introduction

Agriculture is a foundation of the global economy, providing livelihoods for billions while ensuring food security. However, challenges such as climate change, pests, and plant diseases threaten crop yields, with plant diseases alone causing yield losses ranging from approximately 5% to over 40%, depending on crop type, disease severity, and management effectiveness [1][2]. As the global population increases, sustainable food production becomes progressively vital, necessitating innovative strategies to optimize yields and minimize environmental impact. Smart agricultural practices, particularly early disease detection and management, play a crucial role in enhancing productivity and securing global food supplies [3].

Corn, a vital staple crop, is highly susceptible to pathogens, affecting yield at all growth stages. Beyond direct consumption, it is used in products like oil, starch, flour, and biofuel. Disease outbreaks can cause significant losses, leading to food shortages and financial harm [4]. To address this, researchers have leveraged deep learning models, particularly Convolutional Neural Networks (CNNs), for disease detection in corn leaf images. Studies have explored various CNN architectures, including AlexNet, VGG16, VGG19, GoogleNet, Inception-V3, ResNet50, and ResNet101, alongside machine learning methods for classifying corn leaf diseases [5].

Agriculture is vital to the Philippine economy, employing 40% of the workforce and contributing 20% to the GDP. However, crop prediction remains a challenge due to diseases, pests, climate change, and environmental factors, affecting farmers' decisions and livelihoods [6].

Corn is cultivated across 2.5 million hectares, corn yields about eight million metric tons yearly and serves as food, livestock feed, and raw material for industrial products [7]. To enhance agricultural sustainability and increase farmers' incomes, the Philippines is integrating advanced technologies, including the Internet of Things (IoT) and Wireless Sensor Networks. Climate-smart practices such as planting climate-resistant rice, Sloping Agricultural Land Technology (SALT) for soil conservation, and the System of Rice Intensification (SRI) are being adopted to improve productivity [8] .

Region 12 ranks third in white corn production, contributing 11% of the national output, and second in yellow corn production at 18% [7]. However, regional crop analysis shows that irrigated palay remains the dominant crop, with success rates of 52.18% compared to 32.67% for yellow corn and 8.63% for white corn. [6] These findings emphasize the need for further research to enhance agricultural practices and improve production efficiency.

This study aims to develop an artificial intelligence solution using CNNs for classifying corn leaf diseases. Focusing on Polomolok and General Santos City, the research seeks to empower farmers with a valuable tool to enhance disease management, ultimately increasing crop yields and promoting agricultural sustainability.

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II. Literature Review

Convolutional Neural Network (CNN)

CNN has proven to be a highly effective deep learning architecture for image classification, particularly in the detection of corn leaf diseases. By utilizing convolutional layers for feature extraction, pooling layers to reduce complexity, and fully connected layers for final predictions, CNNs excel in recognizing intricate visual patterns in agricultural applications [9]. 8 Studies employing CNN-based models like ResNet34 have demonstrated impressive classification accuracy, reaching up to 97.6% when identifying diseases such as blight, common rust, and gray leaf spot [10] . Similarly, applications like "MaizeCheck" leverage CNNs to provide farmers with a rapid and precise method for monitoring crop health, enhancing disease management, and improving agricultural productivity [11].

To further refine CNN-based disease detection, researchers have explored transfer learning, which enables models to apply knowledge acquired from extensive datasets to specific agricultural challenges [12]. This technique effectively mitigates data scarcity and overfitting issues, as demonstrated by studies that fine-tuned pre-trained CNNs on the PlantVillage dataset, achieving improved classification performance [13]. These advancements further strengthen CNN-based models, improving their reliability and adaptability in agricultural applications. CNNs continue to play a crucial role in deep learning-driven agriculture, providing scalable and efficient solutions for automated disease identification and supporting sustainable farming practices.

Corn Leaf Diseases

Different regions where crops are grown have unique water and soil environments and exhibit differences in temperature and humidity during growing seasons, all of which can affect the pathogen attack process and eventual symptom expression. Hence, commonly diseases would be different based on different environmental factors [14]. The following diseases are the commonly found diseases in the municipality of Polomolok and General Santos City:

Brown Spot, it is caused by the fungus Physoderma maydis. Symptoms of brown spot usually appear on mid-canopy leaves. Leaf lesions are countless, tiny, round to oval, yellowish to brown in color, and usually occur in broad bands across the leaf. [15]

Corn Rust, or common rust, caused by the fungus Puccinia sorghi, is characterized by small, tan spots that develop into elongated, brick-red to cinnamon-brown pustules. This disease is favored by cool temperatures 16-23°C and high relative humidity 100%. corn rust can reduce the functional leaf area and photosynthesis of the corn plant. [16]

Leaf Blight, a significant fungal foliar disease affecting corn globally, is caused by either Exserohilum turcicum, Northern Corn Leaf Blight, or Cochliobolus heterostrophus, Southern Corn Leaf Blight. Characterized by large, cigar-shaped, grayish-tan lesions on leaves, the disease thrives in cool to moderate temperatures and high humidity. In advanced stages, lesions produce numerous spores, giving them a darker appearance. This disease directly impacts photosynthesis, leading to reduced grain filling and potential yield losses of 15-20%, with severe cases exceeding 40% loss. [17] [18]

Maize Streak Virus (MSV), a prevalent plant disease that primarily affects corn crops, causing significant yield losses. It is transmitted by leafhoppers, specifically the species Cicadulina mbila. MSV can also infect over 80 other grass species, highlighting its broad host range and potential impact on various agricultural systems. [19]

Mobile Application Development

Studies have optimized ResNet34 for mobile applications, achieving validation accuracies of 86-95% while enhancing computational efficiency. For tea leaf disease recognition, an improved ResNet34 reached 94.67% test accuracy with a 37.21% reduction in iteration time [20], while a CBAM-ResNet34 model for strawberry classification achieved 92.36% validation and 87.56% testing accuracy [21].

III. Methodology

The objective of this study is to utilize the model ResNet34, for the classification of corn leaf diseases, including Brown Spot, Corn Rust, Healthy, Leaf Blight, and Maize Streak Virus (MSV). The pretrained model is fine-tuned and regularized to optimize accuracy and prevent overfitting. Data augmentation techniques are applied to enhance variability, and the model is trained on a dataset of 27,146 images. Methods and architecture are discussed below.

Data Augmentation

Data augmentation techniques were implemented to simulate real-world variations in image orientation, scale, and lighting. Further, oversampling was used to expand and balance the dataset, ensuring fair representation across all five classifications. The preprocessing and augmentation methods included the following techniques:

Resizing. A preprocessing technique that adjusts image dimensions while maintaining aspect ratio or fitting a required size. In deep learning, resizing ensures images match the network's expected input dimensions, such as 224×224 pixels, standard for CNNs [22]. It standardizes input data, improves computational efficiency, and ensures consistency.

Rotation. Rotating images at ±20 degrees enhances model robustness against real-life variations [23].

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Shift Transformation. Pans images in any direction, filling boundaries with edge pixels or zero values. The applied translation range was ±15% of image dimensions [24].Shear Transformation. Alters image geometry along a specific direction, simulating perspective changes and object deformations. The applied shear range was ±12 degrees [25] .

Zoom Transformation. Enlarges or shrinks images to modify scale, simulating distance variations. The scaling factor ranged from 0.85 to 1.15 [26].Flip Transformation. Reflects images along vertical or horizontal axes, improving generalization. The flipping probability was 50% for both directions [27]. Color Transformation. Adjusts brightness (±40%), contrast and saturation (±20%), and hue (±10%) to simulate varied lighting conditions, enhancing model robustness [28].

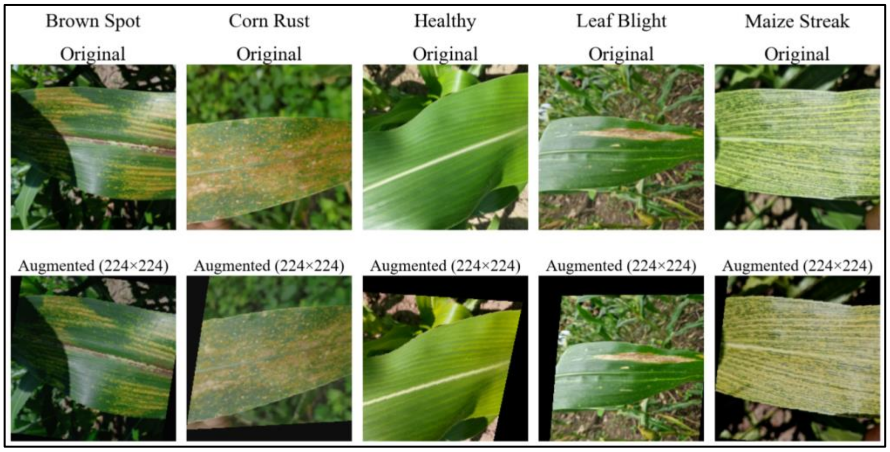

Figure 1. Original and Augmented Images Comparison

Figure. 1 presents a comparison between the original images and their augmented counterparts using various Basic Image Manipulation (BIM) techniques previously described. The augmentations are applied randomly to introduce diverse variations in the training dataset, enhancing the model's ability to generalize. This visualization highlights how each augmentation contributes to increasing data diversity, which is crucial for improving the robustness and accuracy of the CNN model.

Table I. Dataset Total Distribution Per Classification

Classes	Brown Spot	Corn Rust	Healthy	Leaf Blight	Maize Streak
Count	5, 290	5, 506	5, 374	5, 506	5, 470
Total	27, 146 Corn Leaf Images				

Table I presents the collected raw images were augmented to generate 5,290 Brown Spot images, 5,506 Corn Rust images, 5,374 Healthy images, 5,506 Leaf Blight images, and 5,470 Maize Streak images. This augmentation process resulted in a total of 27,146 corn leaf images in the dataset.

ResNet34

ResNet34 offers a balanced approach between depth and computational efficiency. It consists of 16 residual blocks arranged into four groups with increasing feature channels (64, 128, 256, and 512). The network starts with a 7×7 convolutional layer followed by a 3×3 max pooling layer for initial feature extraction, and each residual block uses two 3×3 convolutional layers with batch normalization and ReLU activation. With about 21.8 million trainable parameters, ResNet34 delivers strong performance without high computational demands, making it well-suited for image classification tasks like corn leaf disease detection [29].

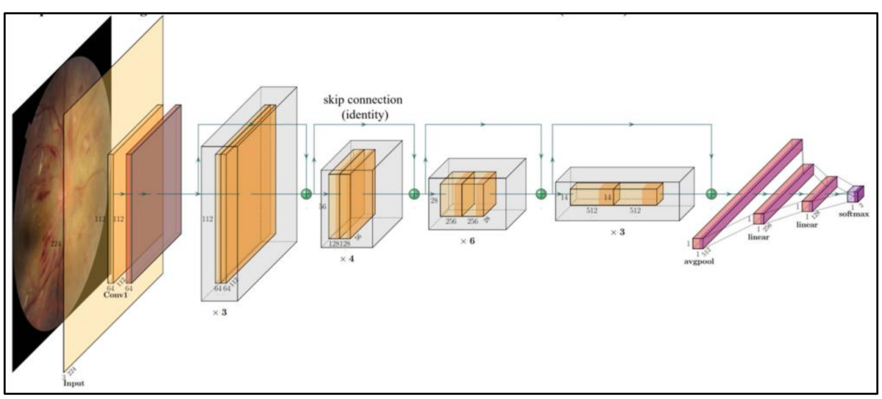

Figure 2. Resnet34 Model Architecture [30]

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The process started with data preprocessing, where a varied dataset of corn leaf images was prepared by resizing, normalizing, and augmenting the images. [28] For model training, ResNet34 model was employed, and the data was divided into training, validation, and testing subsets with a 70%, 15%, and 15% distribution respectively. [31]The training process consisted of 20 epochs.

Fine Tuning

Fine-tuning is a machine learning technique that refines a pre-trained model using a specific dataset, allowing it to adapt to new tasks or improve performance on specialized problems. Instead of training from scratch, fine-tuning adjusts all model parameters based on a smaller, task-focused dataset [32]. In this study, a pre-trained ResNet34 model was fully fine-tuned on corn leaf images, updating every layer to capture unique disease patterns. This comprehensive approach enhanced both low-level feature extraction and high-level classification, leading to improved generalization and more accurate disease detection [33].

Regularization

The researchers devised the following methods to counter overfitting, starting from balancing the dataset through oversampling and data augmentation. AdamW, an optimizer, is essential for improving model performance, accelerating training, and mitigating instability. [34] In this study, AdamW was configured with a learning rate of 0.001 and a weight decay of 0.01, effectively constraining large weight values in the model.

CosineAnnealingLR, a learning rate scheduler, dynamically adjusts the learning rate to guide the model toward an optimal solution. [28] In the experiment, it was implemented with 20 epochs and a minimum learning rate of 1e-6.

Dropout, a method that deactivates portion of neurons per iteration to prevent reliance on specific features and enhance performance on unseen imagesin neural networks, improves generalization in deep learning. This study applied a 0.4 dropout rate. [35].

BIM techniques play a crucial role in enhancing the performance of CNN by increasing the diversity of training data. Techniques such as cropping, flipping, rotation, scaling, and color transformation introduce variations that help the model generalize better to unseen data. [23] In addition, the researchers employed an oversampling technique to address the imbalanced class distribution. [36]. The raw dataset initially contained 1,576 images, distributed unevenly across five disease classifications and was expanded to 27,146 images, with each class containing approximately 5,290 to 5,506 images, ensuring a more balanced and diverse training set.

This study presents an a systematic method to agricultural image classification using a pre-trained ResNet34 model, demonstrating the power of transfer learning in addressing domain-specific challenges. By implementing sophisticated techniques such as comprehensive data augmentation, advanced regularization, and strategic fine-tuning, the study overcomes critical limitations of small agricultural datasets. The framework dramatically expanded the original dataset from 1,576 to 27,146 images through intelligent augmentation and oversampling, ensuring balanced representation across disease classes.

The methodology leverages ResNet34's residual learning architecture to enable deep feature extraction with minimal computational resources. Key optimizations including dropout, AdamW optimization, and CosineAnnealingLR were employed to enhance model generalizability and mitigate overfitting. By fine-tuning all model layers and exposing the network to a diverse range of image variations, the approach significantly improves classification accuracy and robustness, positioning deep learning as a promising solution for agricultural monitoring and disease detection.

Datasets

Table II. Total Corn Leaves Images Collected

Classes	Brown Spot	Corn Rust	Healthy	Leaf Blight	Maize Streak
Olympog	268	121	154	16	221
Lagao				130	
Glamang					177
Landan	1	26		258	1
Mabuhay		142	61		
Total	269	289	215	404	399

Table II shows the number of images for the five classification. In General Santos City, Barangay Olympog gathered 268 Brown Spot, 121 Corn Rust, 154 Healthy, 16 Leaf Blight, and 221 Maize Streak images. Barangay Lagao gathered 130 Leaf Blight images; Barangay Mabuhay has 142 Corn Rust and 61 Healthy images. In Polomolok, Barangay Glamang gathered 177 Maize Streak images, and Barangay Landan gathered 1 Brown Spot, 26 Corn Rust, 258 Leaf Blight, and 1 Maize Streak image. There are 1,576 raw images gathered: 269 Brown Spot, 289 Corn Rust, 215 Healthy, 404 Leaf Blight, and 399 Maize Streak.

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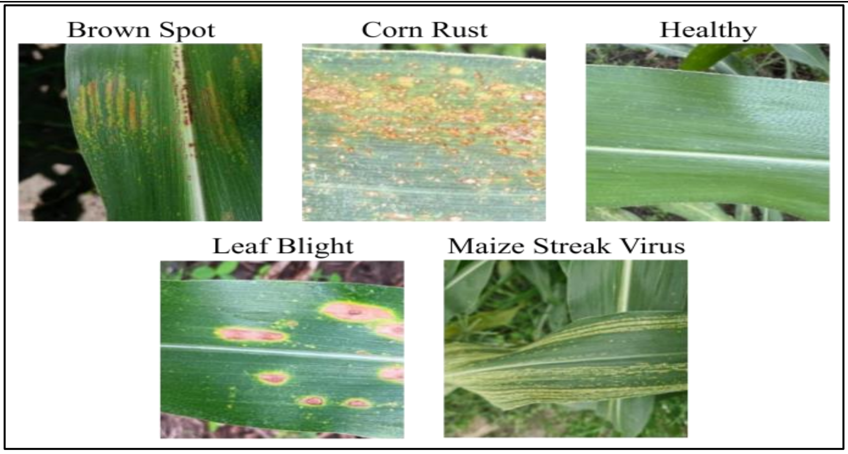

Figure 3. The Five Corn Leaf Classfication

Figure. 3 presents sample images of the five corn leaf disease classifications used in this study: Brown Spot, Corn Rust, Healthy, Leaf Blight, and Maize Streak Virus (MSV). Each image illustrates distinct visual symptoms associated with the respective disease, such as rust-colored pustules, gray lesions, and streak-like patterns. These images serve as reference for model training and validation in the classification of diseased and healthy corn leaves.

The data collection resulted in 1,576 images that represent a diverse distribution of corn leaf diseases across various locations in General Santos City and Polomolok. Notably, images for Banded Leaf and Sheath Blight (BLSB) and Downy Mildew were absent, despite being commonly reported by agricultural experts. This absence could be due to factors such as seasonality, environmental conditions, effective crop management practices like fungicide application and crop rotation, or the possibility that these diseases are more localized in areas not included in the survey [37][38].

The image distribution reveals geographical variability, with certain diseases dominating specific areas—such as high counts of Brown Spot and Maize Streak in Olympog, Leaf Blight in Barangay Landan of Polomolok, and Maize Streak Virus in Glamang. A key concern is the slight imbalance in the dataset, with fewer Healthy samples compared to classes such as Leaf Blight and Maize Streak, which could introduce bias in the CNN's performance. This imbalance was mitigated through a rigorous data augmentation process, thereby enhancing the model's ability to generalize across all categories.

Ethical Considerations

This study involving farmers and agricultural experts has been conducted in accordance with established ethical guidelines and principles. Prior to data collection, explicit informed consent was obtained from all participants. Participants were provided with comprehensive information regarding the research objectives, data collection procedures, and the intended use of images and findings. All participants were assured of their right to withdraw from the study at any time without penalty. Additionally, all personal information collected from respondents has been maintained as strictly confidential and accessible only to the research team.

The researchers declare that there are no conflicts of interest that could bias or compromise the integrity of this research. The research is conducted independently and objectively, with no financial, personal, or professional interests that could influence the findings or recommendations provided to participants. All sources and data from other researchers and experts have been appropriately cited and credited to maintain intellectual property standards and avoid plagiarism.

IV. Results And Discussion

Table III. Classification Report of The Result

Classes	**Brown Spot**	**Corn Rust**	**Healthy**	**Leaf Blight**	**Maize Streak**
Accuracy	98.67%				
Precision	98.76%	98.76%	99.75%	99.88%	95.57%
Recall	98.97%	99.66%	96.45%	98.30%	99.88%
F1-Score	99.35%	99.21%	98.07%	99.09%	97.68%

Table III presents the classification report of ResNet34 model with 98.67% accuracy in classifying corn leaves. Brown Spot attained 99.74% precision and 98.97% recall, resulting in a 99.35% F1-score. Corn Rust attained 98.76% precision and 99.66% recall, resulting in a 99.21% F1-score. Healthy leaves attained 99.75% precision but 96.45% recall, resulting in a 98.07% F1-score, indicating some misclassification. Leaf Blight was almost perfect with 99.88% precision and 98.30% recall, resulting in a 99.09%

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F1-score. Finally, Maize Streak Virus (MSV) attained 95.57% precision and 99.88% recall, resulting in a 97.68% F1-score, indicating very good recall with slightly lower precision.

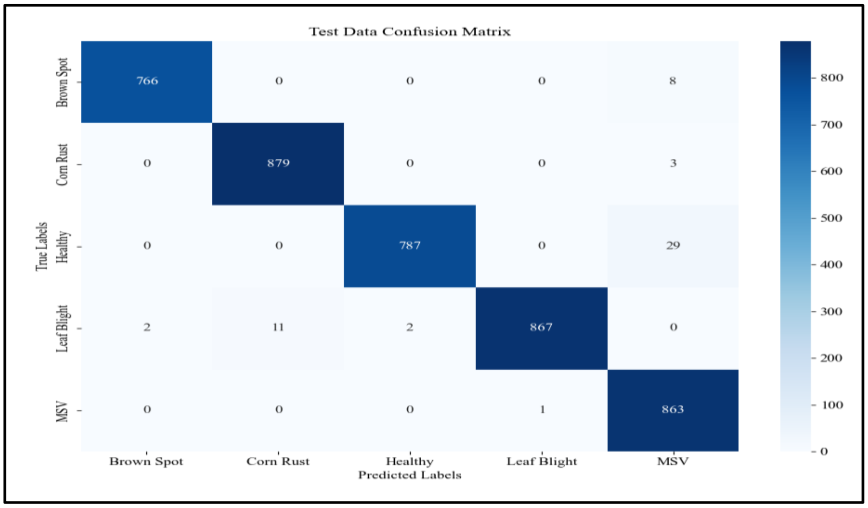

Figure 4. Model's Confusion Matrix

Figure 4. presents the evaluation of the ResNet34 model's accuracy in classifying corn leaf diseases into five categories: Brown Spot, Corn Rust, Healthy, Leaf Blight, and MSV. Out of 4,218 classification tests, the model correctly identified 4,162 cases, achieving an overall accuracy of 98.72%. Most misclassifications involved MSV, with a few cases of Brown Spot, Corn Rust, and Leaf Blight being incorrectly labeled. Despite these occasional errors, the model demonstrated strong performance across all disease categories, effectively distinguishing between different corn leaf conditions.

The high accuracy of 98.67% achieved by ResNet34 aligns with previous studies using similar methodologies and datasets. For instance, a similar study reported a comparable 97.6% accuracy on corn leaf disease classification using ResNet34 and the PlantVillage dataset. This reinforces ResNet34's effectiveness in complex image classification tasks due to its deep residual architecture and mitigation of the vanishing gradient problem.

Transfer learning, leveraging pre-trained ImageNet weights, plays a crucial role in enhancing performance, especially with limited data. Additionally, robust data augmentation techniques—rotation, scaling, and color transformations—improve model generalization. Fine-tuning all ResNet34 layers further strengthens its robustness, aligning with best practices. Prior research highlights that synthetic augmentation and preprocessing significantly contribute to high model accuracy. [10] Given these factors, the study's results confirm ResNet34's reliability for corn leaf disease classification.

Table IV. Comparison of Model Performance

Model	**Accuracy**	**Precision**	**Recall**	**F1 Score**
Resnet34	98.67%	98.74%	98.65%	98.68%
EfficientNet	98.20%	98.17%	95.25%	98.20%
Alexnet	95.76%	95.82%	95.78%	95.70%
VGG19	96.37%	96.65%	96.23%	96.34%
MobilenetV2	96.18%	96.28%	96.06%	96.13%

Table IV illustrates the comparison of the model reveals that ResNet34 is the best-performing architecture with the highest accuracy 98.67%, precision 98.74%, recall 98.65%, and F1 Score 98.68%. This suggests that ResNet34 is the most reliable model for predicting corn leaf diseases, showing a perfect balance between precision and recall to provide the least number of false positives and false negatives. EfficientNet performs closely at 98.20% accuracy but has a lower recall of 95.25%, which implies it tends to miss certain true cases and is therefore less good even with high precision.

Among the rest of the models, VGG19 accuracy 96.37% and MobileNetV2 accuracy 96.18% perform similarly and are thus viable alternatives, although they are still behind ResNet34. AlexNet, having the lowest accuracy 95.76%, has the poorest performance. Although EfficientNet and MobilenetV2 are well-suited for low-resource environments on account of their lightweight architecture, ResNet34 is still the optimal solution for high-accuracy corn leaf disease classification.

The ResNet34 model's exceptional 98.67% accuracy in corn leaf disease classification represents a significant breakthrough for agricultural technology and food security. By enabling early and precise disease detection, the model offers transformative potential for sustainable farming practices. Its remarkable performance—particularly in identifying Brown Spot F1-score 99.35%and Corn

Rust F1-score 99.21%—provides farmers with a powerful tool for targeted intervention, potentially reducing crop losses and minimizing unnecessary pesticide use.

The model demonstrated strong versatility across disease categories, with high recall 96.45% to 99.88%. ResNet34 outperformed other architectures, but the competitive accuracy of EfficientNet 98.20% and MobileNetV2 96.18% highlights their potential for mobile-based disease detection in resource-limited settings. With 99.75% precision in identifying healthy leaves and stable convergence, the model offers a scalable AI-driven solution. Its deployment in agriculture, particularly in developing regions, could enhance disease management and promote sustainable farming practices.

The LeafScan Mobile Application

Following the evaluation process the researchers developed an initial mobile application for the application of the trained model. The application integrates the trained Resnet34 model, allowing users to classify corn leaf diseases using captured or uploaded images. The following figure illustrate key functionalities of the system:

Figure 5. Home Screen of the Mobile Application

Figure. 5 presents the home screen of the mobile application. At the top, the application name "LeafScan" is displayed, followed by an image input box where users can upload an image for disease classification. Below the input box, users can choose between two image input methods: "Take Photo" and "Select from Gallery". At the bottom, the application displays a "Recent Scans" section, showing the history of recently scanned images.

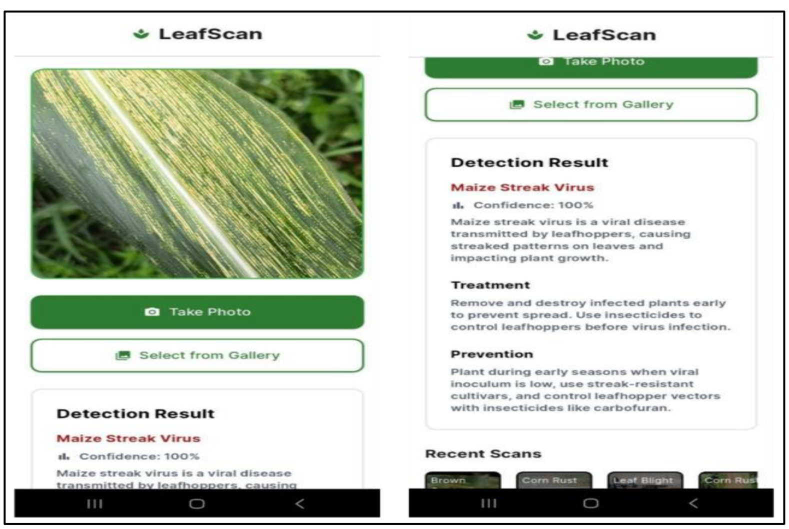

Figure 6. Prediction Result Screen

Figure. 6 displays the prediction result screen after the user selects and submits an image for analysis. The application processes the image and provides the closest classification result along with the model's confidence score. Additionally, the screen presents a brief description of the identified disease, along with suggested treatments and preventive measures to assist the user in managing the disease.

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The LeafScan mobile application prototype successfully implements the ResNet34 model for corn leaf disease classification in a field-deployable format. Developed using Flutter for cross-platform compatibility and optimized with PyTorch Lite, it achieves efficient processing, 1 to 5 seconds, and a storage size of 233 MB [39]. Its offline functionality ensures accessibility for farmers in rural areas with limited internet connectivity [40].

The intuitive interface, featuring image capture, gallery selection, and manipulation tools, enhances usability across different technological literacy levels [41]. While formal User Acceptance Testing (UAT) is pending, preliminary tests confirm the application's core functionality, demonstrating the feasibility of integrating ResNet34 into a mobile platform for agricultural disease diagnosis. Additionally, by incorporating disease descriptions, treatment recommendations, and preventive measures, LeafScan evolves beyond a classification tool into a comprehensive decision support system for sustainable farming [42].

LeafScan represents a significant advancement in corn disease management by integrating a trained ResNet34 model into a Flutter-based mobile platform designed for offline use, addressing challenges faced by rural farmers with limited internet access and low-end devices. Its intuitive interface, with multiple image input methods and adjustments, enhances accessibility across different technological literacy levels. However, the absence of User Acceptance Testing (UAT) limits insight into its real-world viability, leaving uncertainties about its precision in diverse field conditions and alignment with agricultural workflows. While its technical feasibility is evident, practical validation through user testing is necessary. Despite this, LeafScan’s successful model integration into a mobile application offers a promising tool for agricultural education and sustainable farming.

V. Conclusions

Corn leaf diseases such as Brown Spot, Corn Rust, Leaf Blight, and Maize Streak Virus pose significant threats to crop yields, underscoring the need for advanced diagnostic methods. This study evaluated a CNN model based on ResNet34, trained on 27,146 corn leaf images, and achieved an impressive 98.67% classification accuracy. The model’s deep 34-layer architecture and residual connections enhanced its ability to recognize intricate disease patterns, improving classification performance. Furthermore, the successful integration of the trained model into a mobile application demonstrated its feasibility for real-world deployment, confirming its potential for practical agricultural use. These findings highlight the effectiveness of deep learning in plant disease detection and provide a foundation for future research to address challenges such as dataset variability and real-world implementation in farming environments.

Recommendations

Based on the findings of this study, several areas for further research and improvement are recommended to enhance corn leaf disease classification. Developing a fully functional expert system that integrates the trained model with a thoroughly conducted user acceptance test (UAT). Expanding the classification model to include additional corn leaf diseases, such as Banded Leaf and Sheath Blight and downey mildew, would allow it to diagnose a broader range of infections. Additionally, deeper collaboration with agricultural experts, plant pathologists, and local farmers would facilitate more extensive data collection and controlled experiments on disease progression. Addressing these recommendations will help bridge the gap between experimental research and practical applications, ultimately improving disease detection accuracy and enhancing disease management in corn farming.

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