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Image-Based Corn Leaf Disease Detection Framework using Yolov8 Model

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Abstract: Crop diseases pose significant challenges to agricultural production, leading to substantial crop losses. With the increasing demand for food production to meet the needs of a growing population, ensuring the health and productivity of crops like corn is of paramount importance. The proposed framework integrates cutting-edge technologies including computer vision, machine learning, and mobile application development to create a user-friendly and efficient tool to accurately identify and classify diseases affecting corn crops. The framework aims to automate the disease detection process through the analysis of images of corn leaves affected by diseases like northern leaf blight (NLB), gray leaf spot (GLS), and northern leaf spot (NLS) obtained from Kaggle datasets. By utilizing Yolov8 for feature extraction and classification, the system achieves high accuracy in disease detection. The framework is designed to be scalable, adaptable, and efficient, making it suitable for real-time applications in agriculture. Experimental results demonstrate the effectiveness of the proposed approach in accurately diagnosing corn diseases, thereby aiding farmers in timely intervention and crop management. By integrating these advanced technologies into a comprehensive framework, the corn disease detection mobile application aims to provide farmers with a reliable tool for early diagnosis, effective intervention, and improved crop management practices, ultimately enhancing crop yield and ensuring food security.

Keywords*: Corn Leaf Diseases, Disease Detection, YOLOv8, Performance Metrics, Precision Agriculture.*

Introduction

Plant diseases pose a significant threat to global food security by affecting crop yield and quality. Corn, scientifically known as Zea mays, is a staple crop that plays a crucial role in global food security. Furthermore, the role of corn in food security extends beyond its direct consumption as a staple food. Corn is a versatile ingredient in various processed food products, highlighting its significance in the food industry [1]. Moreover, corn-based nutritional products have been studied for their potential benefits in enhancing the health and performance of individuals, including athletes [2].

Corn leaf diseases are a significant threat to corn crops globally, impacting both yield and quality. Diseases such as Southern Leaf Blight (SLB), Northern Leaf Blight (NLB), Gray Leaf Spot (GLS), corn common rust, and corn gray leaf spot are among the most prevalent and damaging diseases affecting corn plants [3], [4], [5]

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The detection and management of diseases affecting corn are paramount in ensuring food sustainability and safety. The detection and classification of corn leaf diseases are crucial for effective disease management and crop protection. Early identification of diseases such as SLB, NLB, and GLS is essential to implement timely control measures and prevent further spread within corn fields [3], [4], [6]

Advancements in technology, such as artificial intelligence and machine learning, have been instrumental in developing innovative approaches for corn leaf disease detection. Deep learning has significantly impacted the field of agriculture by providing robust tools for the detection and classification of plant diseases, including corn leaf diseases. Utilizing deep learning techniques, particularly Convolutional Neural Networks (CNNs), has demonstrated considerable potential in accurately identifying and categorizing various corn leaf diseases [7], [8]. These technologies have shown promise in accurately identifying and classifying corm leaf diseases, enabling farmers to take proactive steps to mitigate the impact of these diseases on crop productivity [6], [9].

Researchers have explored diverse deep-learning models and methodologies to enhance the efficiency and accuracy of disease detection in corn plants. [10] conducted a survey on the application of deep CNNs for predicting plant leaf diseases, emphasizing the importance of deep learning techniques in image recognition. Similarly [11] highlighted the significance of CNNs and transfer learning in identifying plant leaf diseases, stressing the necessity of substantial data for training deep learning networks. [12] optimized a dense CNN model specifically for disease recognition and classification in corn leaves, showcasing the potential of deep learning in monitoring crop health and enhancing crop production. Furthermore, [13], introduced a hybrid model for leaf disease classification based on modified deep transfer learning and ensemble approaches, highlighting the adaptability of deep learning models for agricultural monitoring. These studies collectively underscore the increasing interest and advancements in utilizing deep learning for corn leaf disease detection.

The application of deep learning in agriculture, particularly in plant disease detection, is gaining attraction due to its effectiveness in automating and enhancing the accuracy of disease identification processes [14]. Research has shown that deep learning models, combined with transfer learning and data augmentation techniques, can achieve high accuracy rates in identifying corn diseases like common leaf rust, common rust, northern leaf blight, and healthy leaves [15], [16]. These methods enable early disease diagnosis and targeted interventions, such as precise application of treatments, reducing the reliance on broad-spectrum pesticides, and promoting sustainable agricultural practices. The integration of deep learning for corn leaf detection offers significant promise in advancing food sustainability efforts. By enabling early and accurate disease identification, optimizing resource utilization, and improving crop monitoring capabilities, deep learning technologies have the potential to revolutionize agricultural practices, mitigate crop losses, and contribute to ensuring food security for a growing global population.

With the increasing demand for efficient and accurate detection of diseases affecting corn crops, this study aims to provide a practical solution for farmers and agronomists to monitor and manage crop health effectively. The proposed framework integrates the state-of-the-art YOLOv8 object detection model, renowned for its real-time processing capabilities and high accuracy. YOLO (You Only Look Once) represents a series of convolutional neural network-based models designed for real-time object detection. YOLOv8 is the latest iteration in this series, incorporating advancements to enhance both accuracy and efficiency.

Through the utilization of state-of-the-art algorithms and methodologies, this framework offers a promising solution to the challenges faced in corn leaf disease detection. The proposed framework emphasizes scalability and usability, allowing for seamless integration with mobile and web-based applications. The YOLOv8 model's lightweight architecture enables real-time inference on edge devices, facilitating on-the-field deployment for timely disease monitoring and intervention. Overall, this framework represents a significant advancement in leveraging deep learning techniques for corn disease detection, offering a powerful tool for enhancing crop health management practices and supporting sustainable agriculture.

Methodology

To develop a real-time mobile application for identifying corn leaf diseases, the researcher utilizes deep learning algorithms to precisely and quickly detect different types of corn leaf diseases. The innovative platform was created to provide farmers and other agronomists with an easy-to-use tool that can quickly identify and classify plant diseases, thus enabling timely interventions that guarantee crops' well-being and maximum agricultural output. Merging advanced techniques of image processing with mobile phones, the research work intends to bring scientific innovations from computer vision into agriculture practice. This methodology describes how accurate and efficient detection of various corn leaf diseases on mobile devices could be realized through careful data collection, preprocessing, model selection, and training as well as the development of a mobile application.

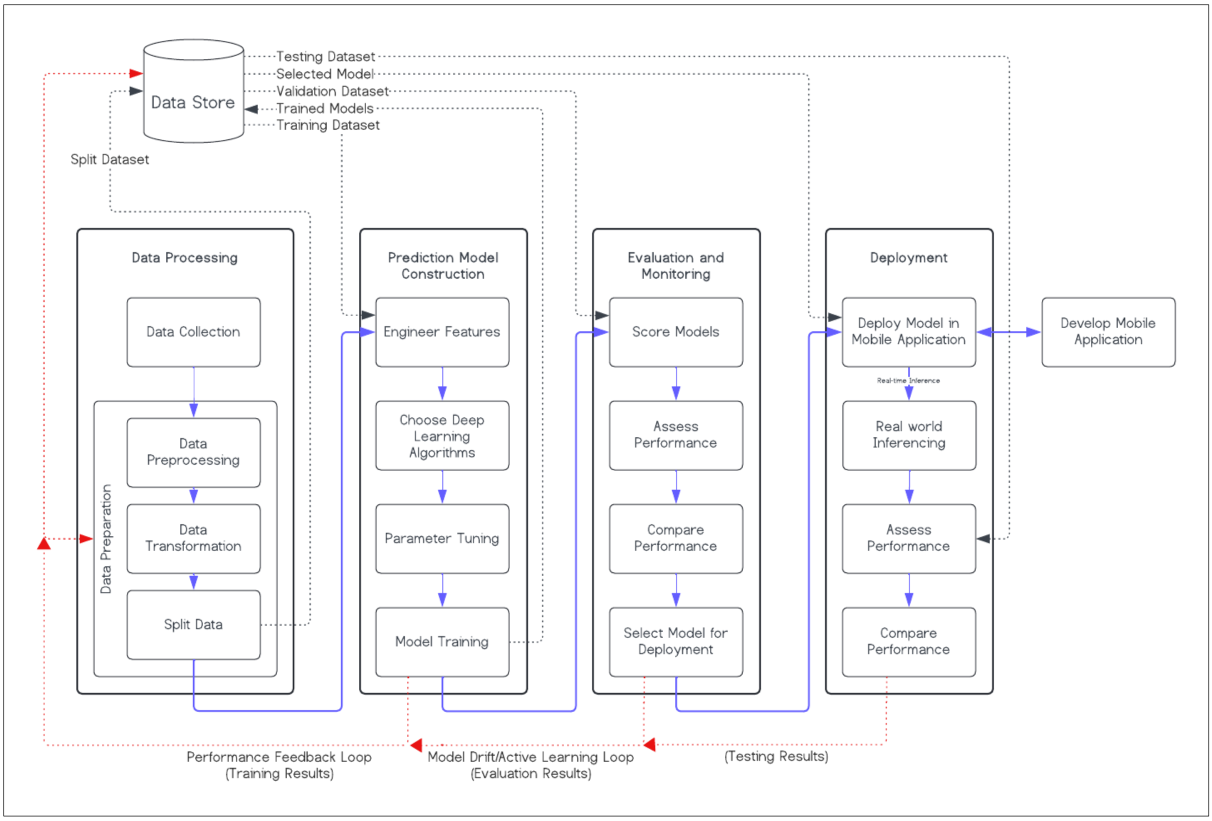

Fig 1. Architecture design of real-time corn leaf disease classification mobile application

The architecture diagram in Figure 1 details the steps involved in creating a corn leaf disease classification model and its deployment into a mobile application, enabling real-time classification. The architecture design provides a comprehensive pipeline for the development and deployment of a corn leaf disease classification model. The process is divided into key stages, including data processing, prediction model construction, evaluation and monitoring, and ultimately, deployment.

Data Processing. Datasets were sourced from PlantVillage dataset, a publicly accessible corn/maize leaf disease repositories. Moreover, the incorporation of raw data collected by researchers via field observations and experiments adds to the density of the dataset. The image dataset undergoes various preprocessing steps, including labelling, resizing, normalization, and augmentation, to make it suitable for model training. Subsequently, the data is divided into training, validation, and testing datasets to support the model development and evaluation process. Notably, the raw data gathered by the researcher is specifically included in the testing dataset. This ensures an independent appraisal of the model's performance, thereby enhancing its reliability and accuracy.

Prediction Model Construction. Constructing a predictive model for corn leaf disease classification begins with feature engineering to identify key image attributes. Techniques like image processing were used to highlight meaningful data patterns. A variety of neural networks with good performances today were selected for experimental comparison to verify the effectiveness of the model namely-ResNet34, MobileNetv2, and YOLOv8. Hyperparameters are optimized using grid search for best performance. Training involves feeding data to the algorithm and adjusting the model until loss and accuracy metrics are satisfactory.

Evaluation and Monitoring. Models for corn leaf disease classification were scored using validation datasets to calculate metrics like accuracy, precision, recall, and F1-score. The models are then evaluated not only for classification accuracy and efficiency but also for their operational speed and resource consumption, important for mobile device deployment. Finally, the models are compared, considering their effectiveness across various disease classes and generalization across diverse datasets.

Deployment. The last step involves integrating the selected deep-learning model into a mobile app for immediate analysis. The app, developed following the agile methodology lifecycle, acts as the interface for user interaction with the model. It allows users to take pictures of corn leaves and submit them for instant disease classification by the embedded deep learning model.

Feedback. The outcomes from the training, evaluation, and testing stages are instrumental in forming a feedback loop that aids in preserving the performance and relevance of the deep learning models in practical applications. All data generated during these stages, along with real-time inference data, are archived in a data store for future reference and analysis. This data store acts as a central repository, thereby aiding in the continuous enhancement and adaptation of the model. The model's performance is continually monitored in real-time during inference and through periodic evaluations using appropriate datasets. Metrics such as accuracy, precision, recall, and F1-score offer insight into the model's efficacy. If the performance dips below acceptable levels, it may necessitate a review and adjustment of the model.

Results And Discussion

In the field of agriculture, maintaining crop health and optimizing production depends on the early identification and precise diagnosis of plant diseases. The development of advanced technologies has revolutionized the way we approach plant disease management. The study aims to develop a mobile detection system in detecting various corn leaf diseases, including Northern Leaf Blight, Southern Leaf Blight, and Grey Leaf Spot. The results of the study will provide insights into the potential of mobile corn leaf detection as a practical and cost-effective tool for disease management in corn fields.

The experimental comparison revealed that YOLOv8 model is the most effective model for corn leaf disease detection. The YOLOv8 model was trained on the annotated dataset, optimizing the loss function to improve detection performance. The model exhibits high precision, recall, accuracy, and F1-scores across all disease categories. As shown in Figure 2, Yolov8 has a recall of 94.81% and a precision of 95.73% which translates to an excellent accuracy of 96.18% and an F1-score of 95.22%. The high-performance metrics achieved by YOLOv8 underscore its efficacy in object detection tasks. The model's balanced trade-off between accuracy and speed makes it well-suited for real-world deployments where timely detection is crucial.

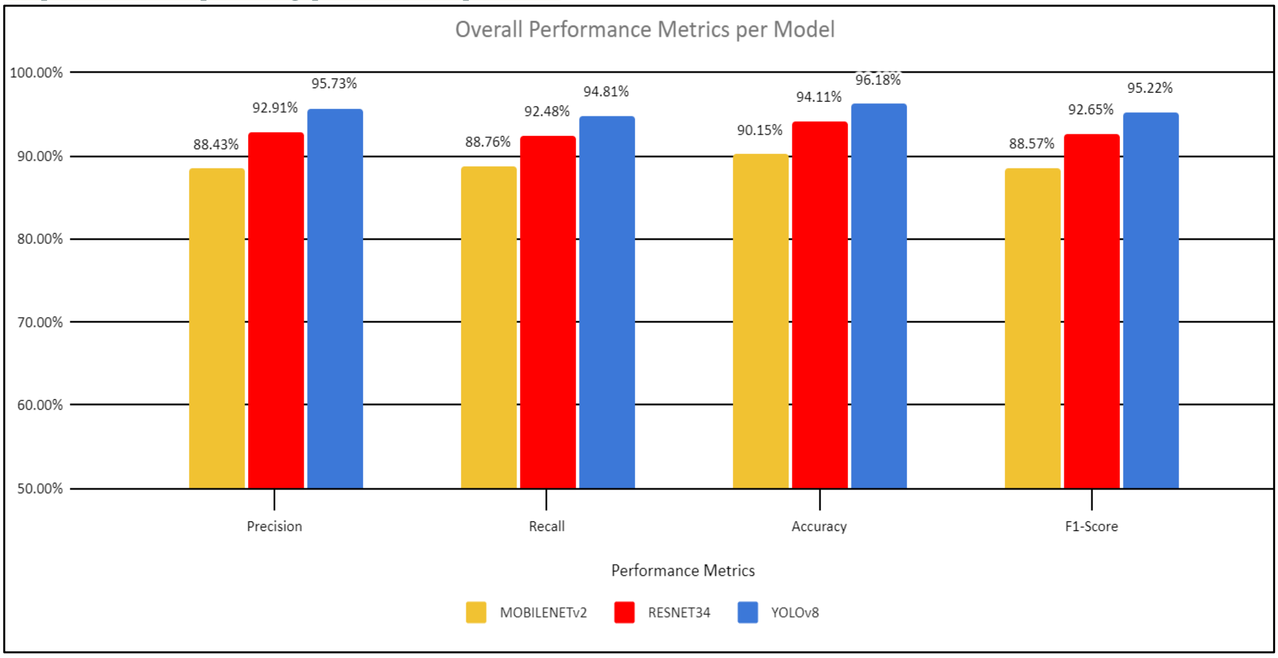

Fig 2. Performance Metrics per Model

Furthermore, confusion matrices reveal that YOLOv8 as shown in Figure 3 effectively discriminates between different disease classes, with minimal misclassifications. During the training phase, Yolov8 consistently identifies corn leaf diseases as revealed in the normalized confusion matrix result. The model has a strong ability to identify diseases such as Blight (0.92), Common Rust (0.97), and Grey Leaf Spot (0.93).

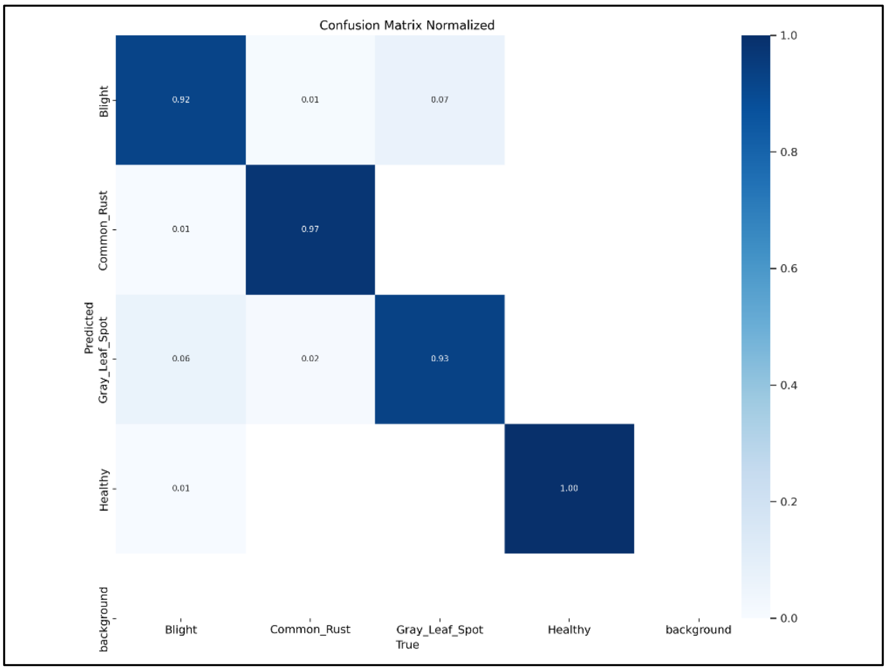

Fig 3. Normalized Confusion Matrix of YOLOv8

Furthermore, experimental results also showed that Yolov8 exhibits convergence, indicating that it is picking up new skills during the training period. The swift inference speed and robust performance of YOLOv8 make it an excellent choice for real-time corn leaf disease classification. YOLOv8, effective for real-time object detection and classification, is suitable for on the go inference[17].

1. System Requirements

The mobile app for corn leaf detection requires a smartphone with a camera to capture images of corn leaves. Mobile-based tools, particularly smartphones, offer novel approaches for disease identification due to their computing power, high-resolution displays, and advanced HD cameras [21]. The app requires sufficient computational power to process images hence a mid-range or high-end smartphone with a decent camera, sufficient processing power, and storage capacity is recommended for optimal performance. The application may require internet connectivity to upload images in the cloud server. However, the app may also have an offline mode that allows users to capture and analyze images without an internet connection, but this feature may not be available in all versions of the app.

2. Design of Prototype

The mobile application is designed to enable users to capture images of corn leaves and request real-time classification using the Yolov8 model as shown in Figure 3. The combination of mobility, adaptability, and convenience makes mobile-based platforms superior to other platforms in various domains, including healthcare, monitoring, and detection applications [18], [19], [20].

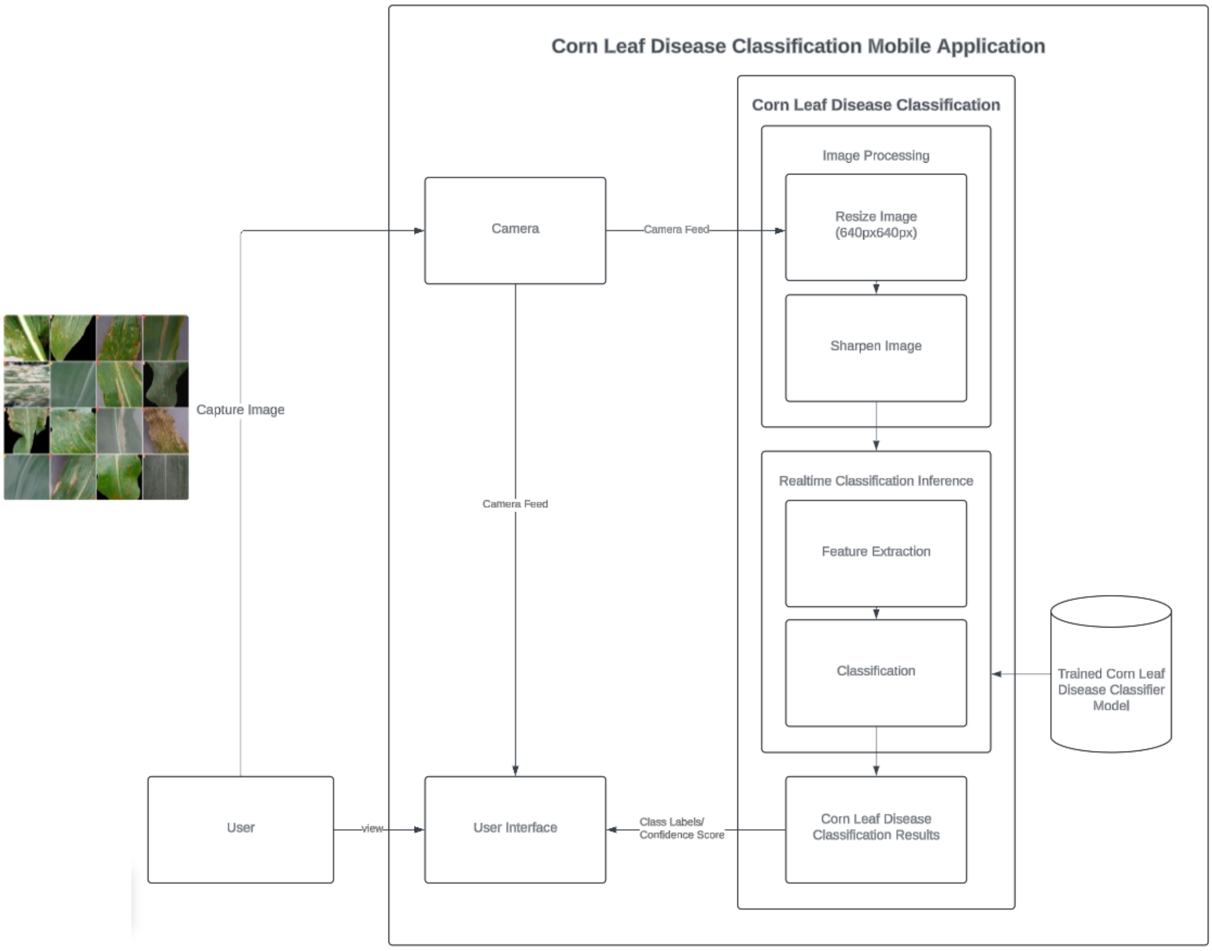

Fig 3. Block Diagram of Corn Leaf Disease Detection

The process begins with the user capturing an image or video of a corn leaf within the mobile application. To capture real-time video or images of corn leaves, the application utilizes the Android Camera API, which allows access to the device's camera to display the live feed within the app and pass the captured data as input to the YOLOv8 model for real-time inferencing.

This image is then preprocessed to improve its quality and ensure that it is suitable for input into the Yolov8. Captured images undergo preprocessing steps, including resizing them to match the input size expected by the model (640x640 pixels). This resizing ensures compatibility with the model's input requirements, facilitating optimal classification accuracy. By standardizing the input size, the application can achieve consistent and reliable results across different devices and environments [17]. Preprocessed images are passed through the YOLOv8 model for inference. During this stage, the model analyzes the images and produces output data, such as bounding boxes, class labels, and confidence scores. Parsing the model's output is essential to extract and interpret the relevant information needed for effective disease classification. The extracted features are fed into a Yolov8 model trained on a dataset of corn leaf images labeled with their corresponding disease types. The model has learned patterns that differentiate between healthy and diseased leaves based on the features extracted.

The model predicts whether the corn leaf in the image is healthy or diseased based on the learned patterns. The output of the model is a classification result that indicates which disease, if any, is present in the leaf. The application employs the model to conduct real-time inference, offering instant insights into the health of a photographed corn leaf subject. The analysis's findings are shown on the smartphone's screen. This contains details on the illness that has been identified, how serious it is, and even suggestions for further testing or therapy. The app allows the user to engage, giving feedback or more details as needed. For example, they could get advice on how to treat the illness, verify the diagnosis, or give more information like the plant's location and growth stage.

The application also incorporates error handling methods to manage potential issues, such as camera or model loading errors. This ensures uninterrupted app performance and provides users with a seamless experience, even in the event of unexpected events.

As the model operates in real-time, its performance is continually evaluated using a testing dataset, inclusive of raw data collected by the researcher. This grants an impartial measure of the model's accuracy in disease classification and allows for constant adjustments to enhance performance.

Conclusion

Mobile-based corn leaf disease detection using Yolov8 model has emerged as a promising solution for farmers and agricultural professionals to diagnose corn leaf diseases accurately and efficiently. The use of the Yolov8 deep learning model has enabled real-time detection of corn leaf diseases with high accuracy and fast inference speed. The development of mobile apps for corn leaf disease detection has made it accessible to a wider audience, enabling farmers to diagnose diseases in the field and take appropriate actions to prevent their spread. However, the development of mobile-based corn leaf disease detection is challenging. It takes money and effort to gather a sizable and varied dataset of photos of corn leaves. Deep learning knowledge and high-performance computing resources are needed for preprocessing the dataset and optimizing the deep learning models. Understanding cross-platform frameworks and mobile app development is necessary for implementing the approach in a mobile application. But despite these difficulties, mobile-based corn leaf disease detection app have the power to completely change how farmers identify and treat corn leaf diseases. By using a trained deep learning model to analyze images of corn leaves, the mobile application can provide real-time feedback and recommendations for managing and treating any diseases that are detected.

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