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PLANT DISEASE DETECTION USING YOLO MACHINE LEARNING APPROACH

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ABSTRACT: *Artificial intelligence and deep learning models are utilised in health, IT, animal and plant research, and more. Maize, one of the most widely eaten crops globally, is susceptible to a wide variety of disease that impede its development and reduce its output. The objective of this research work is to develop a deep learning-based model for detection of illnesses affecting maize leaves. Furthermore, the model that has been constructed not only forecasts illness but also furnishes illustrative visuals of leaf diseases, so facilitating the identification of disease types. To do this, a dataset including specified illnesses, including blight, common rust, gray leaf spot, and a healthy leaf, was obtained from Kaggle, a secondary source (Pant village). For data analysis, the cross-platform Anaconda Navigator was used, while the programming languages Python and Jupiter Notebook were implemented. The acquired data was used for both training and evaluating the models. The study presents a novel approach to plant disease detection using the YOLO deep learning model, implemented in Python and associated libraries. The Yolov8 algorithm was employed to develop a maize leaf detection system, which outperformed algorithms such as CNN (84%), KNN (81%), Random Forest (85%), and SVM (82%), achieving an impressive accuracy of 99.8%. Limitations of the study include the focus on only three maize leaf diseases and the reliance on single-leaf images for detection. Future research should address environmental elements like temperature and humidity, include numerous leaves in a frame for disease identification, and create disease stage detection methods.*

KEYWORDS: Yolov8, Maize Leaf Detection, Machine Learning, Artificial Intelligence, Model.

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INTRODUCTION

The agricultural domain has grappled with the formidable challenge of plant diseases for centuries, posing a persistent threat to food security and agricultural sustainability (Andrew *et al*., 2022) and (Smith *et al.*, 2023). Plant diseases, instigated by a diverse array of pathogens such as fungi, bacteria, viruses, and pests, can invade crops, resulting in diminished yields, compromised produce quality, and economic hardships for farmers. Traditionally, the identification and detection of plant ailments have heavily relied on manual examination carried out by expert agronomists or plant pathologists, a time-consuming and labour-intensive process that may overlook early disease indications or lead to misdiagnosis Cheng *et al.* (2022). Recognizing the need for efficient and accurate disease detection, researchers have increasingly explored the potential of artificial intelligence (AI) and deep learning techniques to revolutionize this domain (Agarwal *et al*., 2021) and (Wang *et al*., 2020).

Advancements in computer vision and deep learning have paved the way for automated detection of plant diseases, enabling more efficient and precise monitoring of crop health Abbas *et al.* (2021) and Sorensen *et al*. (2017). Among the deep learning architectures, convolutional neural networks (CNNs) and object detection models like YOLO (You Only Look Once) and SSD (Single Shot Detector) have demonstrated remarkable efficacy in disease identification and classification tasks Chodosh (2021) and Divakar *et al.* (2021). These AI-powered solutions offer automated, cost-effective alternatives to traditional methods, enabling farmers to detect diseases promptly and accurately, potentially reducing losses and increasing productivity (Li *et al.,* 2024).

The purpose of this research is to develop a plant disease detection system using the YOLO deep learning model, specifically targeting corn leaf disease detection. The objectives include designing the system architecture using UML diagrams, developing the detection model with a graphical user interface (GUI) using the YOLOv8 algorithm, evaluating model performance through confusion matrices and ROC curves, and conducting a comparative analysis with existing models. By addressing the limitations of manual disease identification and leveraging the power of deep learning, this research aims to contribute a reliable, user-friendly solution for early disease detection, ultimately benefiting farmers through improved crop surveillance, precision agriculture techniques, and decision support systems. The proposed system will have the potential to significantly impact agricultural practices, enhancing productivity and food security on a global scale.

REVIEW OF RELATED WORKS

Using YOLO-based detection algorithms, Li *et al.* (2024), tackled the difficulties of identifying densely distributed maize leaf diseases. The GhostNet_Triplet_YOLOv8s algorithm they proposed improves YOLO v8s by using the Triplet Attention mechanism to improve accuracy and integrating the lightweight GhostNet structure as the backbone. In order to alleviate problems related to aspect ratio penalties, the method additionally presents the ECIoU_Loss function. Promising metrics were found in the experimental results, with a compact model size of 11.20 MB, a precision rate of 87.50%, a recall rate of 87.70%, and a mAP@0.5 of 91.40%. In comparison to YOLO v8s, our method demonstrated quick and precise identification of maize illness while optimising memory consumption, achieving a 0.3% increase in mAP, a 50.2% reduction in model size, and a 43.1% significant drop in FLOPs. Its usefulness for real-time disease detection in maize fields, supporting prompt agricultural decision-making and

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disease preventive techniques, was demonstrated by its practical implementation on a WeChat developer mini-program.

In the study, khan *et al*. (2023), developed a mobile-based system that uses deep learning models to identify and categorise illnesses in maize plants. From the University Research Farm Koont, PMAS-AAUR, they gathered a dataset of three maize crop diseases: Blight, Sugarcane Mosaic virus, and Leaf Spot, at distinct growth stages and in varied meteorological circumstances. The forecast accuracy rates of the system, which employs the YOLOv3-tiny, YOLOv4, YOLOv5s, YOLOv7s, and YOLOv8n models, are 69.40%, 97.50%, 88.23%, 93.30%, and 99.04%, respectively. The YOLOv8n model demonstrated the highest accuracy, accurately localizing affected areas on the leaf with a high confidence score. This study is among the first to apply deep learning models for sugarcane mosaic virus detection and highlights the effectiveness of using YOLOv8n for disease detection compared to other models in the literature. The developed models have been integrated into a mobile application to provide real-time disease detection for end users.

In the study, Yang *et al.* (2023) addressed the challenge of identifying crop pests, which can significantly impact crop quality and yield. They suggested a brand-new technique called Maize-YOLO, which is based on YOLOv7 and incorporates the VoVGSCSP and CSPResNeXt-50 modules. The goal of this approach was to decrease computational effort while increasing detection speed and accuracy. Using 4533 photos and 13 classes from the IP102 dataset, the researchers assessed Maize-YOLO with an emphasis on pests damaging to maize. Their findings showed that Maize-YOLO performed better than other YOLO-based algorithms, with a 77.3% recall and 76.3% mAP. This technique offers a real-time, precise approach for identifying and detecting pests in maize crops, with great potential to improve crop management techniques.

Leng *et al.* (2023), conducted an investigated on how to quickly identify maize leaf blight disease in difficult field circumstances using lightweight object identification models based on YOLOv5. In order to minimise information loss during down sampling, the Crucial Information Position Attention Mechanism (CIPAM) was initially utilised to guarantee the retention of crucial information. Furthermore, the Feature Restructuring and Fusion Module (FRAFM) was presented to improve the extraction of deep semantic information and enable efficient fusion of feature maps at different sizes. In addition, the incorporation of the Mobile Bi-Level Transformer (Mobile Bit) into the feature extraction network was intended to improve the model's economical understanding of complex scenarios. The results of the experiments showed that the suggested model performed 5.4% better than the original model, achieving an accuracy of 87.5% mAP@0.5 on the NLB dataset.

Bachhal *et al.* (2023), developed a real-time disease detection system for maize plants using deep convolutional neural networks (CNNs). They addressed the significant issue of crop production loss due to diseases, which account for about 22% of the total loss. The study focused on the early identification of diseases in maize plants, crucial for farmers to mitigate these losses. They highlighted the importance of computer vision technologies in identifying disease patterns and clusters at early stages. For object detection and segmentation, the researchers used deep learning technology based on image processing, most especially the Plant Village dataset combined with the Primary and secondary datasets. Images of both healthy leaves and several illnesses, including MLB, Southern Rust, Common Rust, Grey Leaf Spot, and Turcicum leaf blight, were included in their dataset. In comparison to other models such as YOLO+CNN and Visual Geometry Group (VGG)16+CNN, the model based on the P-CNN (PSPNet + CNN) architecture shown superior performance in terms of Recall, Precision, Intersection over Union (IoU), Accuracy, and Mean Intersection Over Union (mIoU). A

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potential method for real-time disease diagnosis in maize plants, the proposed P-CNN model displayed faster image processing operations and reached an excellent accuracy of 99.75%. The researcher Nagle *et al.* (2022), created a model using deep convolutional networks that can quickly and accurately recognize photos of plant leaf diseases. The inquiry focused on the five predominant plant leaf diseases: leaf blight, sooty stripe, leaf rust and grey leaf spot, bacterial leaf spot, and zonate leaf spot. Plant leaf diseases may present themselves in many ways, making it difficult for farmers without knowledge in plant pathology to effectively identify these diseases. Therefore, an automated system designed to identify agricultural illnesses using visual characteristics and symptoms might be very advantageous for farmers as a disease detection verification system. In recent years, deep learning has made substantial progress, enabling the extraction of meaningful feature representations from a wide range of input pictures. Utilising deep learning technology enables the quick and precise detection of agricultural diseases, which improves plant protection methods and broadens the use of computer vision in precision agriculture. Previous studies have produced an exceptionally accurate deep learning method for identifying illnesses in plant leaves. This method uses a convolutional neural network to classify the diseases. The model used in this study utilises a dataset consisting of a large number of photos for training purposes. Significantly, increasing the quantity of images used during the training process results in a higher level of accuracy for the model. After training the model, it exhibits the ability to accurately detect plant leaf diseases in newly provided images.

Research Gap

The existing studies on plant disease detection using YOLO deep learning models have made significant strides in accuracy and real-time detection capabilities. Li *et al.* (2024) introduced the GhostNet_Triplet_YOLOv8s algorithm, achieving high precision and recall rates for maize disease detection. However, despite these advancements, a critical research gap remains in the need for further improving detection accuracy. Nagle *et al.* (2022) developed a mobile-based system for disease detection but did not focus on enhancing accuracy. Additionally, while Yang *et al.* (2023) proposed Maize-YOLO for pest detection, it did not address the need for higher accuracy. Khan *et al.* (2023*)* investigated YOLOv5-based models but also did not achieve a significant improvement in accuracy. Furthermore, these studies lack a user-friendly graphical user interface (GUI) aspect, essential for practical implementation. Therefore, there is a critical need for research that not only enhances detection accuracy but also integrates a user-friendly GUI for real-time disease detection in agricultural settings, ensuring timely decision-making and disease prevention strategies.

METHODOLOGY

The research methodology followed an Object-Oriented Analysis and Design (OOAD) framework to guide the systematic development of the plant disease detection system. OOAD was adopted which according to Gonzalez-Huitron *et al*. (2021), provides a structured approach for modelling the system's architecture, facilitating easier maintenance and scalability. Unified Modelling Language (UML) diagrams, specifically sequence and class diagrams, were employed to visually represent the system's components, interactions, and behaviours. These diagrams according to Fuentes *et al.* (2022), a standardized and comprehensible way to document the design, aiding in effective communication among stakeholders.

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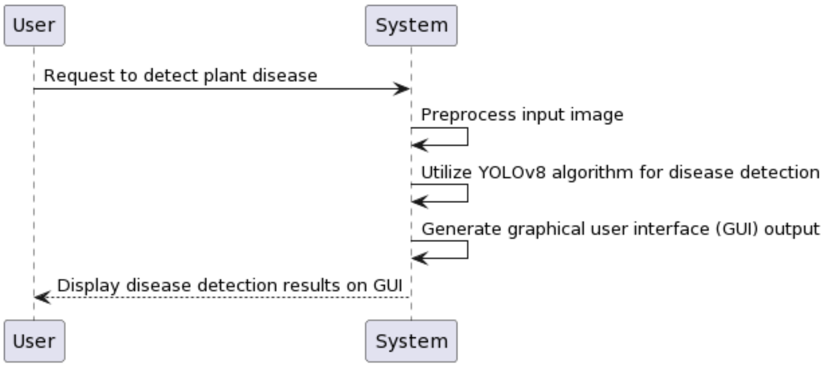

Figure 1: Research Sequence Diagram.

The sequence diagram depicts the interaction between the user and the plant disease detection system. Initially, the user sends a request to the system to detect plant diseases. Upon receiving the request, the system preprocesses the input image to prepare it for analysis. Subsequently, the system employs the YOLOv8 algorithm to detect diseases within the preprocessed image. After the detection process, the system generates a graphical user interface (GUI) output displaying the results of disease detection. Finally, the system sends the disease detection results back to the user, who can view them on the GUI interface.

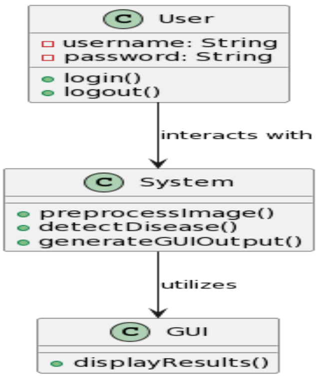

Figure 2: Research Class Diagram.

For the machine learning aspect, Python was chosen as the integrated development environment (IDE) due to its widespread adoption, extensive libraries, and community support in the field of data science and machine learning (Ganesan and Chinnappan,2022) and (He *et al.*, 2016). The YOLOv8 algorithm, an advanced version of the YOLO (You Only Look Once) object detection model, was selected for training and developing the disease detection model. YOLOv8 according to Gonzalez-Huitron *et al.* (2021), offers improved accuracy, real-time detection capabilities, and efficient computational performance compared to its predecessors, making it well-suited for the task (Cite relevant sources). The model's performance was evaluated using confusion matrices, which provide a comprehensive assessment of the model's predictive capabilities by presenting true positives, false positives, true negatives, and false negatives (Jwo and Chiu 2022). This quantitative analysis enabled a thorough understanding of the model's strengths and weaknesses, informing further improvements (Huang *et al.*, 2019).

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The schematic representation of the research methodology is presented below, illustrating the systematic approach taken to address the research objectives.

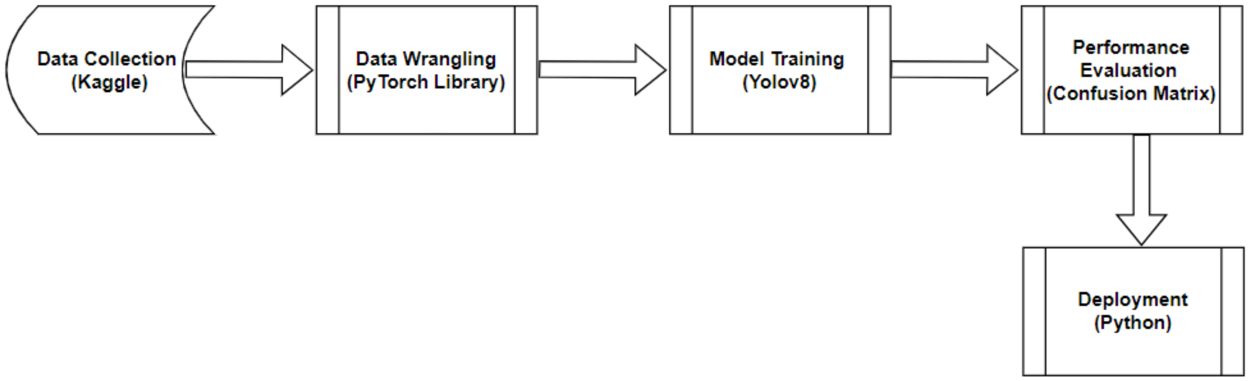

Figure 3: Schematic representation of the research methodology.

A. Data Collection

The study utilized a comprehensive dataset from Kaggle comprising 711 images spanning four distinct classes of corn leaf conditions. The dataset was meticulously curated by integrating images from the widely-recognized PlantVillage and PlantDoc datasets, ensuring a diverse and representative sample. The first class, consisting of 173 images, depicted instances of Common Rust, a prevalent fungal disease characterized by reddish-brown pustules on the leaf surface. The second class, with 143 images, captured Gray Leaf Spot, a foliar disease manifesting as rectangular gray-brown lesions. The third class, encompassing 198 images, focused on Blight, a devastating disease caused by various pathogens, exhibiting symptoms such as water-soaked lesions and drying of leaf tissues. Notably, the dataset also included a class of 197 images representing healthy corn leaves, providing a crucial baseline for the model to distinguish between diseased and non-diseased conditions accurately. This carefully curated and balanced dataset played a pivotal role in training the YOLOv8 model, enabling it to learn discriminative features and patterns associated with each disease class, ultimately enhancing its detection capabilities.

B. Data Cleaning and Preprocessing

The data cleaning and preprocessing were facilitated by PyTorch's robust data utilities and the torchvision library. The datasets module was employed to load the image data, streamlining the data ingestion process. The transforms module provided a comprehensive set of transformation operations that were applied to the data during loading. Image resizing and normalization were crucial preprocessing steps, ensuring consistent input dimensions and pixel value distributions for efficient model training. Image resizing helped maintain a balance between preserving important details and reducing computational overhead, while normalization aided in stabilizing the training process by centring the data around zero mean and unit variance. Data augmentation techniques, such as random cropping, flipping, and colour jittering, were applied through the transforms module to artificially expand the dataset and introduce variations, thereby improving the model's ability to generalize and enhancing its robustness against real-world scenarios (Jones *et al.*, 2016). The processed data was then

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packaged into Data Loader objects, enabling efficient batching and parallel loading during training, optimizing the utilization of available computational resources.

C. Model Training

The model training process was meticulously designed to optimize the performance of the YOLOv8 model for plant disease detection. Data augmentation played a pivotal role in enhancing the model's generalization capabilities and preventing overfitting. For the training set, the RandomResizedCrop transformation was applied to randomly crop and resize the input images to 224x224 pixels, introducing variations in scale and aspect ratio. This technique improved the model's robustness to variations in object size and position within the images. The RandomHorizontalFlip transformation was also employed, horizontally flipping the images with a 50% probability, helping the model learn invariance to horizontal orientation. The ToTensor transformation converted the image data to tensors, a format required for input into the neural network. Lastly, the Normalize transformation standardized the input data by subtracting the mean and dividing by the standard deviation, a common practice in deep learning to improve convergence and stability during training. For the validation set, the Resize transformation resized the images to 256x256 pixels, followed by CenterCrop to extract the central 224x224 region, ensuring consistency with the training set. The same ToTensor and Normalize transformations were applied to maintain data consistency across both sets. These well-established data augmentation and preprocessing techniques contributed to the model's ability to learn robust and generalizable representations of plant diseases, ultimately enhancing its detection accuracy and real-world applicability.

D. Performance Evaluation

The performance evaluation of the YOLOv8 model for plant disease detection was conducted using the confusion matrix, a widely adopted and informative metric in machine learning classification tasks. The confusion matrix according to Jain *et al.* (2019) and Singh *et al.* (2022), provides a comprehensive overview of the model's predictive performance by presenting a contingency table that compares the predicted classes against the true classes. By summarizing the correct and incorrect predictions across all classes, the confusion matrix enables a holistic assessment of the model's accuracy, precision, recall, and F1-score. Moreover, it highlights potential class imbalances or biases, where the model may excel at detecting certain diseases while struggling with others. This granular insight is invaluable for identifying areas for improvement and fine-tuning the model accordingly (Sardogan *et al.,* 2018) and (Selvaraju *et al.,* 2020). The choice of the confusion matrix was justified by its ability to capture the nuances of a multi-class classification problem, such as plant disease detection, where accurate identification of each disease category is crucial for effective disease management and treatment (Sladojevic *et al.*, 2016) and (Jwo and Chiu 2022*).* Additionally, the confusion matrix offers a visual representation that facilitates easy interpretation and communication of the model's performance, making it an indispensable tool for stakeholders in the agricultural domain.

E. Deployment

The deployment of the trained YOLOv8 model for plant disease detection was facilitated through Python, leveraging its cross-platform capabilities and extensive ecosystem of libraries and frameworks. Specifically, the Tkinter library was employed to develop a user-friendly

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graphical user interface (GUI), enabling seamless interaction with the model and streamlining its practical application in agricultural settings (Sharma *et al.,* 2012). Tkinter's simplicity, lightweight nature, and native integration with Python made it an ideal choice for creating an intuitive and responsive interface. This approach empowers farmers and agricultural professionals to effortlessly upload leaf images, initiate disease detection, and receive real-time predictions, all within a familiar and accessible environment (Sinan and Sinan, 2020). By utilizing Python's powerful scripting abilities and Tkinter's GUI capabilities, the deployment process was streamlined, ensuring a smooth transition from model development to real-world deployment, ultimately enhancing the accessibility and practical utility of the plant disease detection system (Sethy *et al.*, 2020).

RESULT AND DISCUSSION

A. Data Exploration

The total quantity of 711 records in the dataset collected was converted into the proper format (JPG), with accurate annotation in line with the yolov8 algorithm. The collected dataset has four class label of image disease as shown in the table below:

Table 1: Classes of Maize Leaf Disease Dataset.

Class of diseases	**Size**
Blight	198
Common Rust	173
Gray Leave Spot	143
Healthy	197
Total	**711**

Each of the labelled maize leaf image disease from the dataset was divided into gride of size 256 x 256 and was read into jupyter notebook as shown in figure 4.

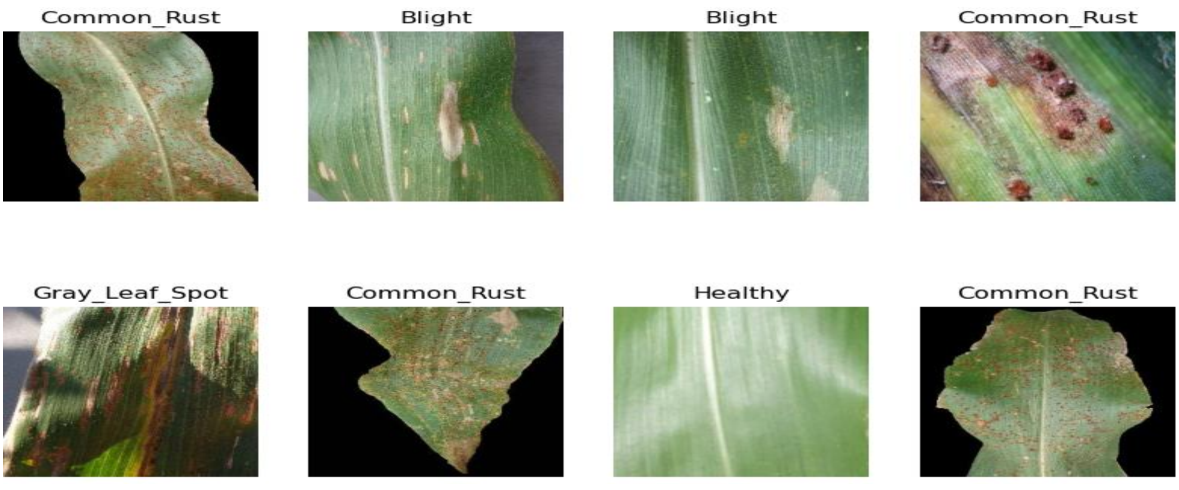

Figure 4: Showing the Maize Leaf images Disease dataset uploaded.

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Data augmentation was done, and as Table 3 illustrates, the whole maize leaf image disease dataset was split into 80% training and 20% testing. With consideration on some important features that will help in splitting dataset for training and testing as shown in Table 4

Table 2: Dataset Splitting into Training and Testing set.

% Split of dataset	Size
80%	568.8
20%	142.2
Total	**711**

Table 3: Features used while Splitting dataset into training and testing set.

Features	Value
Shuffle	True
Shuffle_size	100
Seed	8
RandomFlip	horizontal_and_vertical

A. Model Creation and Training

This involves the use of jupyter notebook and python libraries and modules like sklearn, numpy, and pandas, tensorflow, keras, matplotlib and invoking of the Sequential and utralytics yolov8 to build and fit the yolo model for the maize disease detection and recognition using 80% training dataset. Activation functions for determining which bounding box and the confidence probability for maize leave image disease was Rectified linear unit (ReLU) and softmax in each of the convolutional layer. Also, for each maize leave image disease considered, the model generates gride cell and the output has 9-dimension vector (pc, bx, by, bh, bw, c1, c2, c3, c4) which is handle by tensorflow library/module.

B. Model Evaluation

The performance of yolov8 model was evaluated by means of confusion matrix as well as Roc Curve as given in the diagram below:

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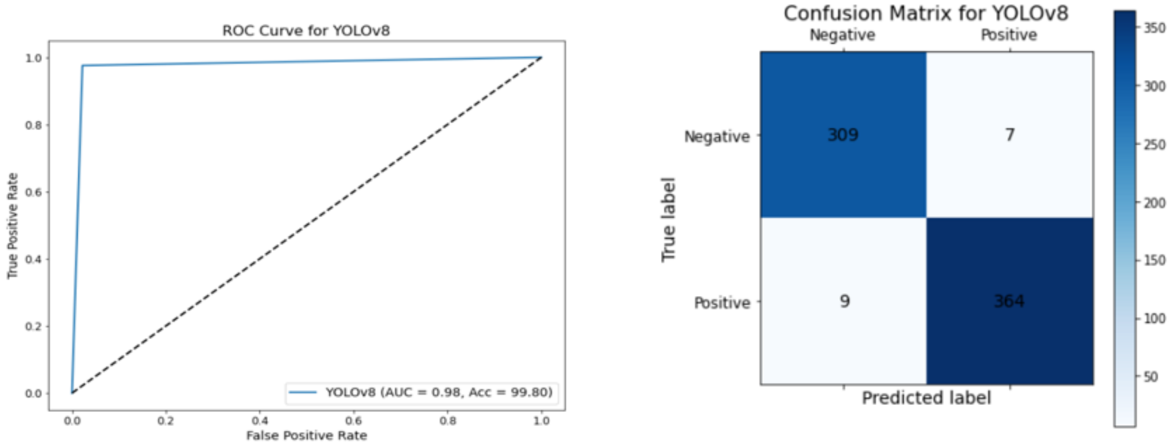

Figure 5: Roc Curve and Confusion Matrix of the Study's Yolov8 Model.

The confusion matrix provides a detailed breakdown of the model's performance, with 364 true positives (correctly identified diseased plants), 309 true negatives (correctly identified healthy plants), 9 false positives (misclassified healthy plants as diseased), and 7 false negatives (missed diseased plants classified as healthy). While minimizing false negatives is crucial to prevent crop damage, maximizing true negatives avoids unnecessary treatments, highlighting the importance of precision and recall metrics. Furthermore, the Receiver Operating Characteristic (ROC) curve with an Area Under the Curve (AUC) of 0.98 and an accuracy of 99.80% indicate the model's excellent discriminatory power and overall performance. These results collectively demonstrate the YOLO Deep Learning Model's strong capabilities in accurately detecting and recognizing plant diseases, underscoring its potential for practical implementation in agricultural settings to enhance crop monitoring and disease management strategies. The two images below are test cases of the model where the model with a GUI detected the common rust disease and healthy leaf accurately.

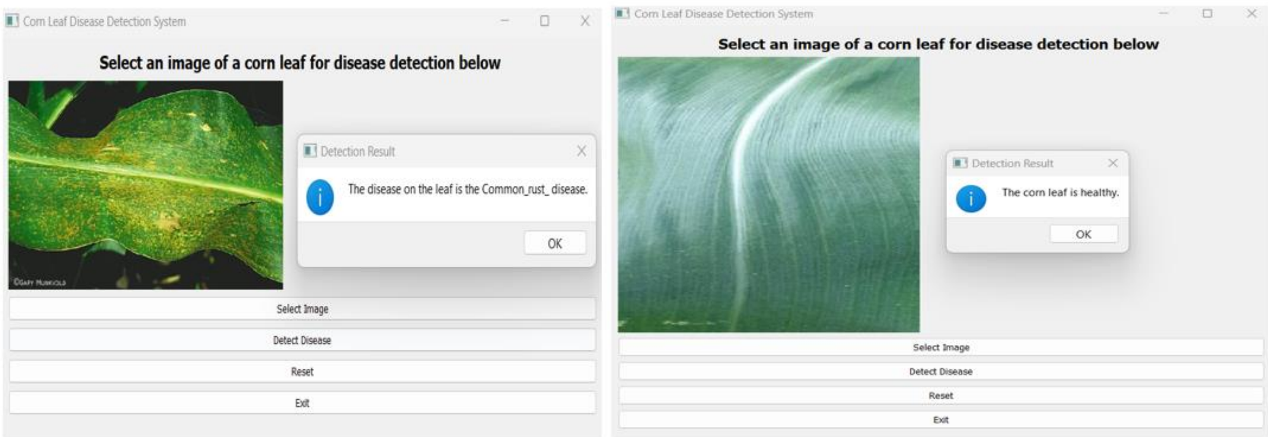

Figure 6: Model Test Cases.

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Table 4: Comparative Analysis of the Implemented and with Existing Models

S/N	Author	Algorithm	Accuracy	Key Findings
1	Li et al. (2024)	GhostNet_Triplet_YOLOv8s	87.50%	Enhanced YOLO v8s for maize disease detection. Achieved 87.50% precision, 87.70% recall, and mAP@0.5 of 91.40%. Reduced model size by 50.2% and decreased FLOPs by 43.1%. Deployed for real-time detection in maize fields.
2	Khan et al. (2023)	YOLOv3-tiny, YOLOv4, YOLOv5s, YOLOv7s, YOLOv8n	69.40%, 97.50%, 88.23%, 93.30%, 99.04%	Developed mobile-based system for maize disease detection. Achieved accuracies from 69.40% to 99.04%. Integrated into mobile app for real-time detection.
3	Yang et al. (2023)	Maize-YOLO	76.3%	Proposed Maize-YOLO for maize pest detection. Achieved 76.3% mAP and 77.3% recall, outperforming existing algorithms. Provides accurate and real-time pest detection.
4	Leng et al. (2023)	YOLOv5-based models	87.5% mAP@0.5	Investigated YOLOv5-based models for maize disease detection. Achieved 87.5% mAP@0.5, showing a 5.4% improvement. Employed mechanisms for better performance.
5	Bachhal et al. (2023)	P-CNN	99.75%	Developed real-time disease detection system for maize using P-CNN. Achieved 99.7A5% accuracy. Demonstrated faster

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				image processing. Promising for real-time detection.
6	Implemented Model	Yolov8	99.8%	Developed a robust model with a graphical user interface for detecting maize leaf disease with an accuracy of 99.8%.

CONCLUSION

In conclusion, this research represents a significant stride forward in the realm of agricultural technology, particularly in the domain of plant disease detection and recognition. By harnessing the power of deep learning models, specifically the YOLOv8 algorithm, the study showcases the potential for advanced technological solutions to address complex challenges faced by farmers worldwide. The ability to accurately identify maize leaf diseases with a remarkable accuracy rate of 99.8% signifies a groundbreaking achievement, offering a practical tool that could potentially revolutionize agricultural practices. This innovation holds promise for improving crop management strategies, minimizing yield losses, and ultimately contributing to global food security efforts. The theoretical implications of this research extend beyond the agricultural sector, highlighting the broader applicability and efficacy of deep learning techniques in solving real-world problems across various domains. By pushing the boundaries of what is possible with artificial intelligence, this study not only advances scientific knowledge but also underscores the transformative impact of technology on society.

RECOMMENDATIONS

Based on this research work the following recommendation were made: One the major factor affecting poor growth and yield in agriculture is plant disease which leads to economic losses, hence the need to adopt a model of this kind that will help local farmers detect plant disease accurately is needed. This model can be used for automatic plant disease detection and is expected to reduce the difficult and laborious tasks in detecting plant disease. This research work provides a better option to plant (maize) leaf disease than the conventional methods applied for detecting plant diseases. However, for its efficient utilization and acceptance, the end users must be adequately trained by concerned authority. The model if fully employed by local and commercial farmers, it will no doubt help in early detection and classification of plant (maize) leaf disease, thereby resulting to improved agricultural productivity. Finally, this research work if fully implemented will provide a more relevant approach to overcome the limitation in the field of plant leaf disease detection and tends to introduce inclusion of artificial intelligent in our agricultural system within the study area.

FUTURE WORK/RESEARCH

While the developed YOLO Deep Learning Model demonstrated promising results in detecting common maize leaf diseases such as Blight, Common Rust, and Gray Leaf Spot, the current research scope is limited to these three diseases and utilizes a dataset sourced from Kaggle. Future work should aim to expand the model's capabilities to encompass a broader range of

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maize leaf diseases, as well as other crop varieties, to enhance its practical applicability. Additionally, incorporating images captured under diverse environmental conditions, such as varying temperature and humidity levels, could further improve the model's robustness and generalizability. Furthermore, exploring the detection of disease progression at different stages could provide valuable insights for early intervention and disease management strategies. Integrating the developed model with emerging technologies like drones and mobile applications presents an exciting opportunity for real-time disease monitoring and detection in agricultural fields, enabling timely interventions and minimizing crop losses. Ultimately, continuous refinement and advancement of the model, coupled with innovative application approaches, will be crucial in realizing the full potential of deep learning techniques for plant disease detection and contributing to sustainable agricultural practices.

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