

# Comparative Performance Analysis of YOLOv8 Model and Traditional Machine Learning Models for Maize Leaf Disease Detection

Rosemary Ngozi Ariwa<sup>1</sup>, Joshua Babatunde Agbogun<sup>2</sup>, Monday Jubrin Abdullahi<sup>3</sup>, Temidayo Oluwatosin Omotehinwa<sup>4</sup>, Bethel Ugochukwu Nnamani<sup>5</sup>, Daniel Gabriel Zhetu<sup>6</sup>, Umar Gambo Abubakar<sup>7</sup>  
<sup>1,2,5,6,7</sup>Department of Mathematical Sciences, Taraba State University, P.M.B. 1167, Jalingo, Nigeria.

<sup>3</sup>Department of Computer Science, Faculty of Computing, Air Force Institute of Technology, P.M.B. 2104, Kaduna North, Kaduna, Nigeria.

<sup>4</sup>Department of Mathematics and Computer Science, Federal University of Health Sciences, P.M.B. 145, Otuokpo, Nigeria.

ariwarosemary@gmail.com<sup>1</sup>, agbogunjoshua@tsuniversity.edu.ng<sup>2</sup>, temidayo.omotehinwa@fuhso.edu.ng<sup>3</sup>, m.abdullahi@afit.edu.ng<sup>4</sup>, annamani.ugo@tsuniversity.edu.ng<sup>5</sup>, dgzhetu@gmail.com<sup>6</sup>, maimuri2020@gmail.com<sup>7</sup>

## Abstract

*This paper titled “Performance Evaluation of Yolo version 8 Model and Some Machine Learning Models for Maize Leaf Disease Detection” presents a novel approach to plant disease detection using You Only Look Once (YOLO) machine learning model, implemented in Python and associated libraries. The study is only concerned with performance evaluation of Yolo version eight model and other existing models using Confusion Matrix and Receiver Operating Characteristic (ROC) curve. For data analysis, the cross-platform Anaconda Navigator was used, while the programming language Python was used. The acquired data was used for both training and evaluating the model. The performance of yolov8 model was evaluated by means of confusion matrix as well as Roc Curve with other machine learning models, the roc curve is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied, it plots the True Positive Rate against the False Positive Rate at different thresholds. The model is evaluated at various threshold, where each threshold gives a different level of confidence in the prediction. The You Only Look Once (YOLO) version8 algorithm was employed to develop a Maize leaf detection system, which outperformed algorithms such as Convolutional neural network (84%), K-Nearest Neighbor (81%), Random Forest (85%), and Support Vector Machine (82%), achieving an impressive accuracy of 99.80%. Future work should explore the inclusion of multiple leaves in a single frame for disease detection, consider environmental factors such as temperature and humidity and develop approaches for detecting disease stages.*

**Keywords:** Random Forest, Support Vector Machine, Disease, Detection, Machine Learning.

## 1. Introduction

The identification and mitigation of plant leaf infections contribute to the reduction of crop production, as stated by Sethy *et al.* (2020), to effectively control plant diseases, it is crucial to employ an early and accurate diagnosis. In the past, the sole method for discerning plant leaf ailments was through manual inspection and evaluation of leaf texture. In recent years, however, Artificial Intelligence (AI) technologies have made it a center of research in this field.

Recent years have seen the widespread use of deep learning in several fields, including intelligent transportation, face recognition, and autonomous driving. By using deep learning algorithms to detect and identify plant illnesses, the constraints of conventional diagnostic methods may be significantly surmounted, resulting in a notable improvement in the precision of such processes. As a result, this phenomenon has attracted significant interest from both scholars and professionals (Li *et al.*, 2022)

Agricultural research is increasingly using artificial intelligence and deep learning-based approaches owing to their ability to independently extract significant characteristics from picture datasets, in addition to their improved speed and accuracy in comparison to traditional techniques (Cheng *et al.*, 2022). One of the most well-known deep learning (DL) architectures is the convolutional neural network (CNN). Currently, leaf disease identification and classification are being done using a variety of deep learning-based techniques. Among these methods are the You Only Look Once (YOLO) approach, the Single Shot Detector (SSD) and another model (Sinan & Uğ 2020), (Ponnusamy *et al.*, 2020), (Ganesan & Chinnappan 2022).

Manual identification of plant illnesses is laborious and prone to errors. Current methods lack reliability in detecting and preventing the spread of plant diseases. Plant disease can cause huge amount of loss in the agricultural domain leading to reduction of grain yield, low consumer preference and decrease in market value. By using advanced techniques such as machine learning and deep learning offer potential solutions for prompt disease detection.

YOLO (You Only Look Once) is a deep learning model that is very important for plant disease identification and diagnosis in agricultural contexts.

Artificial Intelligence can help by making better tools for crop surveillance, designing robots to deliver pesticides and better software to help in breeding for traits like disease resistance. It will help in implementing Precision Agriculture techniques by precisely identifying and localizing disease affected areas within a crop. YOLO offers an automated and cost-effective alternative, eliminating the need for extensive human intervention. It enables farmers to detect diseases promptly and accurately, potentially reducing losses and increasing productivity. It can be integrated into a decision support system for farmers, providing real-time information about disease occurrence, severity, and distribution within a field.

## 2. 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 v8 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 mean Average Precision (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 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 categorize 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 investigation on how to quickly identify maize leaf blight disease in difficult field circumstances using lightweight object identification models based on YOLOv5. In order to minimize 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 (MobileBit) 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 Turicum 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 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 Nagale *et al.* (2021) 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.

With the tremendous advancement of agricultural technology, Wadnere and Ramteke (2022) said, cell phones have emerged as a practical tool for farmers to identify illnesses and insect pests. Scientists have created compact software or mobile applications that empower farmers to detect and recognise crop pests and illnesses. The technology may rapidly provide users with diagnostic results, similarity, disease features, causes, preventive, and management strategies by collecting and uploading photographs of the afflicted crop. By using this scientific methodology, farmers may efficiently address illnesses and insect infestations, hence enhancing crop productivity. The Faster R-CNN has been enhanced by increasing the dimensions of the input layer from  $32 \times 32$  pixels to  $600 \times 600$  pixels. In addition, scientists have devised an automated technique for identifying and recognising leaf markings disease in sugar beetroot plants. The system categorizes the disease severity into three levels: mild, moderate, and severe.

A deep transfer learning approach has been used to construct an enhanced ResNet50 model (CDCNNv2) for better categorization of agricultural diseases and insect pests. This model integrates a categorization system that precisely assesses the magnitude of agricultural diseases and insect pests. The system not only provides real-time and completely automated detection of agricultural pests and diseases, but also offers several auxiliary features like preventative and management suggestions, as well as medication recommendations. The platform has attained a mean precision of 96.84% in detecting five distinct tomato leaf ailments, outperforming other models like VGG16, ResNet50, and SENet by margins ranging from 2.25% to 11.58%. The convolutional neural network architecture has been modified and enhanced using the typical LeNet-5 network as a foundation. This has led to the development of a convolutional neural network system specifically built for the identification of ginger illness. The system utilises data from four distinct forms of ginger disease that have been gathered in their natural habitat. The accuracy rate for identifying the four categories of ginger illnesses was 96%. The detection of 5 kinds of apple leaf diseases has been accomplished using transfer learning and the Faster R-CNN technique. A system for identifying illnesses in apple leaves has been created for the Android platform. It achieves an average accuracy of 76.55% in recognising apple leaf diseases.

The mobile network implemented on mobile phones has achieved an average identification accuracy of 87.5% for the 6 different kinds of grape sick leaves gathered in the field. The mean computation time for an individual image was 134 milliseconds. The system demonstrated an identification accuracy over 80% for a total of 27 illnesses across 6 crops in both laboratory and field settings.

### 3. Methodology

The first step in the dataset collection process is to identify a suitable dataset that encompasses a variety of crops and plant diseases. These datasets provide labeled images of healthy maize and various classes of maize diseases, making them suitable candidates for training the YOLO model.

The caliber and variety of the training dataset have a major impact on the performance of any deep learning model. In order to guarantee that the dataset is suitable for training the YOLO deep learning model for Maize disease detection, we outline the dataset collection method, along with the crucial preprocessing steps that were used. An essential step in getting the dataset ready for training is data preparation.

The total number 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 Table 1.

Table1: Classes of maize leave disease dataset

<b>Class of diseases</b>	<b>size</b>
Blight	198
Common Rust	173
Gray Leave Spot	143
Healthy	197
<b>Total</b>	<b>711</b>

Data augmentation was conducted, where the entire maize leave image disease dataset was divided into 80% of the training dataset and 20% of the testing dataset, as shown in Table 2 with consideration on some important features that will help in splitting dataset for training and testing

Table 2: Dataset splitting into training and testing set

<b>% Split of dataset</b>	<b>size</b>
80%	568.8
20%	142.2
<b>Total</b>	<b>711</b>

By introducing such variations, the model becomes more robust and better equipped to handle variations in real-world data. 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.

### 3.1 Technique for Gathering Data

The procedure used to gather the data was a secondary method which was gotten from Kaggle.com and Plant Village dataset.

#### 3.1.1 Data Analysis Tools and Programming Tools

The tools used for the data analysis is anaconda navigator cross platform and the programming tools used is python programming language and associated libraries like Jupiter notebook.

#### 3.1.2 Techniques for Performance Evaluation

The Receiver Operating Characteristic (ROC) curve is a representation of how a binary classification model performs. It sets the True Positive Rate (Sensitivity) against the False Positive Rate (1 - Specificity) at different thresholds.

This is how it works:

- The model is tested at different thresholds where each threshold represents a unique level of confidence in the predictions.
- For every threshold, there are True Positives (TP), False Positives (FP), True Negatives (TN), and False Negatives (FN).
- Using the following equations, True Positive Rate (TPR) and False Positive Rate (FPR) are calculated:

$$TPR = TP / (TP + FN)$$

$$FPR = FP / (FP + TN)$$

- Also, on the x-axis and y-axis respectively, plot the FPR and TPR to obtain the ROC curve.
- The true positive rate and false positive rate at different thresholds are demonstrated by this curve.
- A perfect classifier would have an ROC curve passing through the top-left corner where TPR equals 1 and FPR equals 0.

- Moreover, the area under the ROC curve (AUC-ROC) measures how well a model distinguishes between positive and negative classes. A higher AUC-ROC means better performance

In addition to these explanations of an AUC-ROC you can also:

- Evaluate how your model performed in various thresholds
- Compare the performance of different models
- Select the optimal threshold for your specific problem

## 4. Results and discussion

### 4.1 Model Evaluation

Implemented Model

The performance of yolov8 model was evaluated by means of confusion matrix as well as Roc Curve

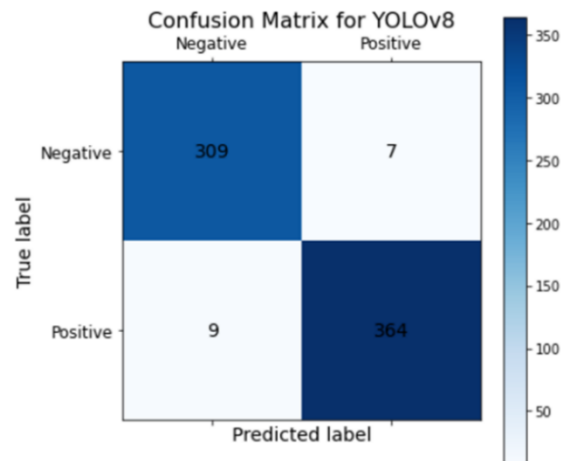


Figure 1: Confusion Matrix for YOLOv8

The confusion matrix in Figure 1 above provides a critical insight into the performance of the model. The True Positive (TP) value of 364 indicates the number of instances where the model correctly identified diseased plants. The True Negative (TN) value of 309 represents the instances where the model correctly identified healthy plants. The False Positive (FP) value of 9 signifies the cases where the model incorrectly classified healthy plants as diseased. Conversely, the False Negative (FN) value of 7 indicates the instances where the model wrongly classified diseased plants as healthy. These values are crucial for evaluating the model's performance, with a focus on minimizing FN (missing diseased plants) to prevent potential crop damage and maximizing TN (correctly identifying healthy plants) to avoid unnecessary treatments, showcasing the importance of precision and recall metrics in this context.

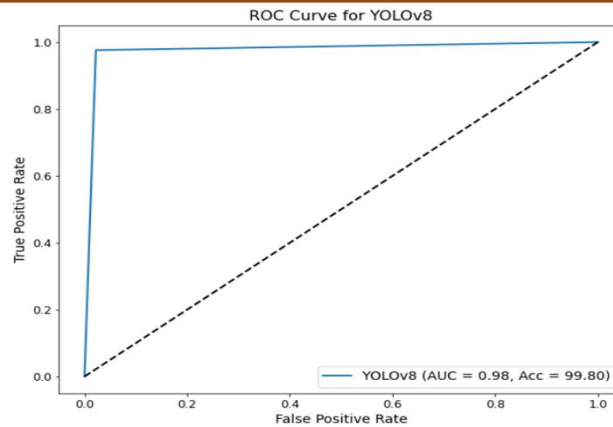


Figure 2: Roc Curve for YOLOv8

The Receiver Operating Characteristic (ROC) curve in Figure 2 above is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied (Omotehinwa *et al.*, 2023). The Area Under the Curve (AUC) value of 0.98 as illustrated in the figure above suggests that the model has excellent discriminatory power, with a high probability of ranking a randomly chosen positive instance higher than a randomly chosen negative instance. This indicates that the model is highly effective at distinguishing between diseased and healthy plants. The Accuracy (ACC) value of 99.80% further supports the model's performance, indicating that it correctly classifies 99.80% of the instances. These results collectively demonstrate the YOLO Deep Learning Model's strong performance in plant disease detection and recognition, with high precision and reliability.

#### 4.2 CNN Model

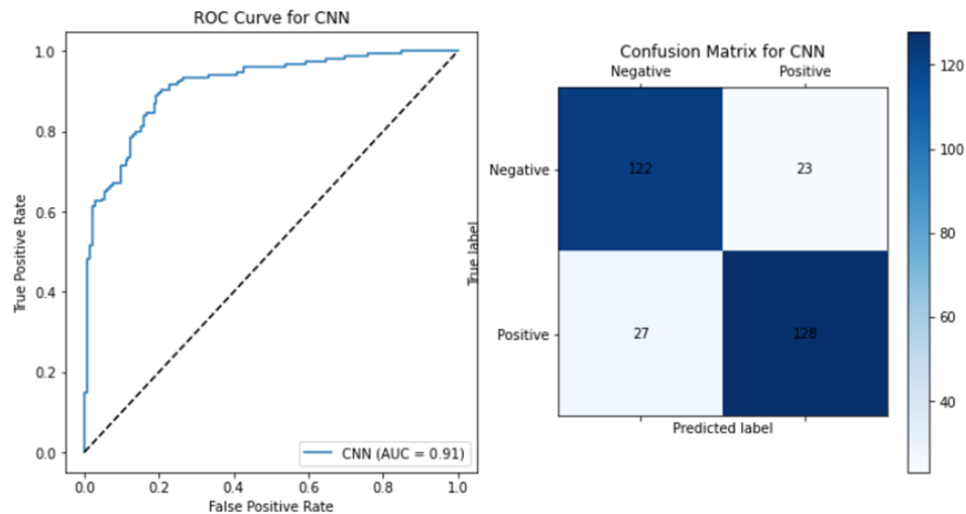


Figure 3: Roc Curve and Confusion Matrix for CNN Model

In the context of a Convolutional Neural Network (CNN) model, as illustrated in Fig. 3 above, the ROC curve with an Area Under the Curve (AUC) of 0.91 indicates a strong performance in distinguishing between classes (diseased and healthy plants in this case). The True Negative (TN)

value of 122 represents the instances where the model correctly identified healthy plants, while the False Negative (FN) value of 23 indicates cases where diseased plants were incorrectly classified as healthy. The True Positive (TP) value of 128 signifies correct identifications of diseased plants, and the False Positive (FP) value of 27 represents cases where healthy plants were mistakenly classified as diseased. These metrics are crucial for evaluating the model's performance, with a focus on minimizing FN (missed diseased plants) to prevent potential crop damage and maximizing TN (correctly identifying healthy plants) to avoid unnecessary treatments, highlighting the model's effectiveness in plant disease detection.

### 4.3 KNN Model

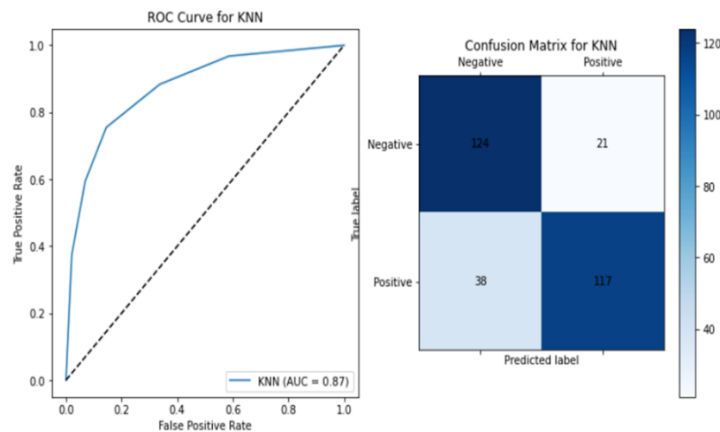


Figure 4: Roc Curve and Confusion Matrix for KNN Model

For the K-Nearest Neighbors (KNN) model in Fig. 4 above, the Area Under the Curve (AUC) of 0.87 indicates good discriminatory power in distinguishing between diseased and healthy plants. The True Negative (TN) value of 124 represents the instances where the model correctly identified healthy plants, while the False Negative (FN) value of 21 indicates cases where diseased plants were incorrectly classified as healthy. The True Positive (TP) value of 117 signifies correct identifications of diseased plants, and the False Positive (FP) value of 38 represents cases where healthy plants were mistakenly classified as diseased. These metrics collectively provide insight into the model's performance, with a focus on minimizing FN (missed diseased plants) and maximizing TN (correctly identifying healthy plants) to ensure effective plant disease detection

#### 4.4 Random Forest Model

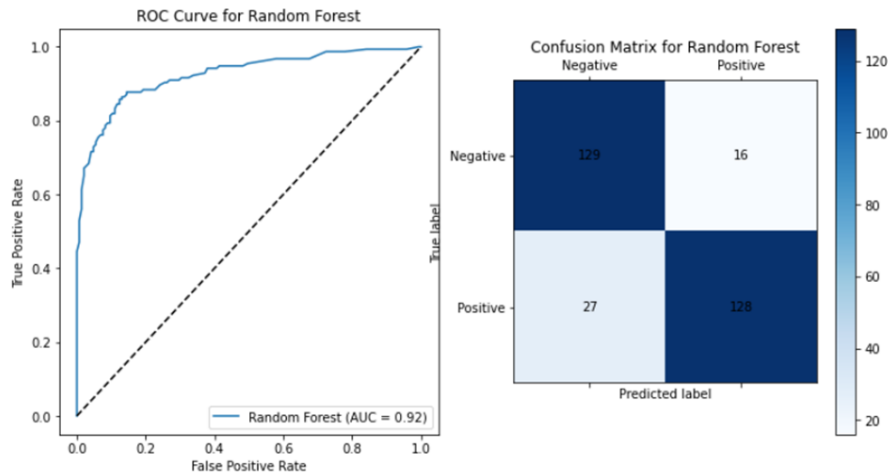


Figure 5: Roc Curve and Confusion Matrix for Random Forest Model

For the Random Forest model in Figure 5 above, the Area Under the Curve (AUC) of 0.92 indicates strong discriminatory ability in distinguishing between diseased and healthy plants. The True Negative (TN) value of 129 represents the instances where the model correctly identified healthy plants, while the False Negative (FN) value of 16 indicates cases where diseased plants were incorrectly classified as healthy. The True Positive (TP) value of 128 signifies correct identifications of diseased plants, and the False Positive (FP) value of 27 represents cases where healthy plants were mistakenly classified as diseased. These metrics collectively demonstrate the Random Forest model's effectiveness in plant disease detection, with a focus on minimizing FN (missed diseased plants) and maximizing TN (correctly identifying healthy plants) for accurate and reliable results

#### 4.5 SVM Model

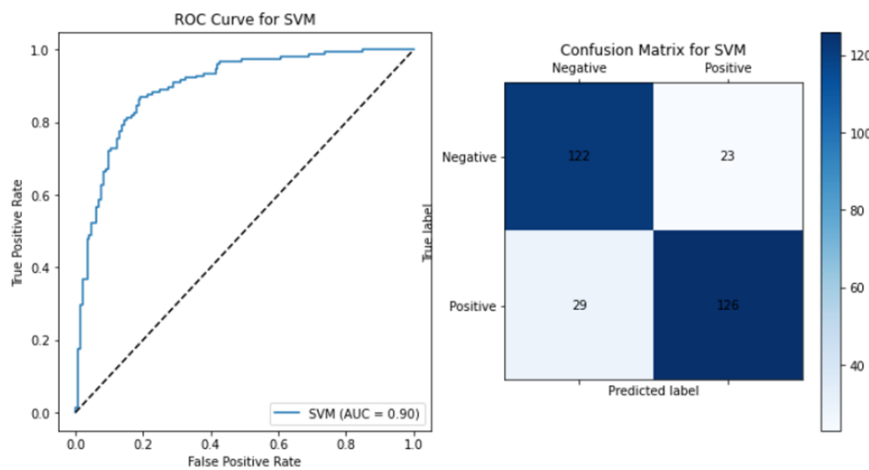


Figure 6: Roc curve and Confusion Matrix for SVM Model

For the Support Vector Machine (SVM) model in Figure 6 above, the Area Under the Curve (AUC) of 0.90 indicates good discriminatory power in distinguishing between diseased and healthy plants. The True Negative (TN) value of 122 represents the instances where the model correctly identified healthy plants, while the False Negative (FN) value of 23 indicates cases where diseased plants were incorrectly classified as healthy. The True Positive (TP) value of 126 signifies correct identifications of diseased plants, and the False Positive (FP) value of 29 represents cases where healthy plants were mistakenly classified as diseased. These metrics collectively show the SVM model's effectiveness in plant disease detection, with a focus on minimizing FN (missed diseased plants) and maximizing TN (correctly identifying healthy plants) for accurate and reliable results.

#### 4.6 Comparative Analysis of Accuracy Across Algorithms

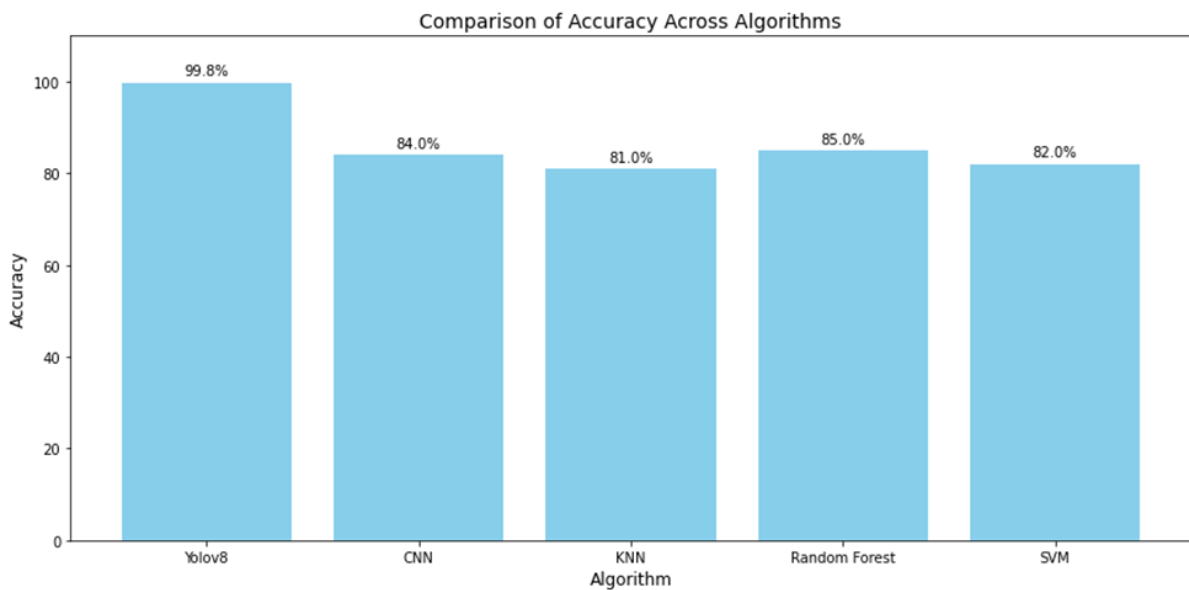


Figure 7: Comparison of Accuracy across Algorithms

In the comparative analysis of the results in Fig. 7 above, it's evident that YOLOv8 achieves the highest accuracy of 99.8%, showcasing its superior performance in plant disease detection. This suggests that deep learning models like YOLOv8 are highly effective in capturing intricate patterns and features, leading to precise classifications. However, traditional machine learning algorithms such as CNN, KNN, Random Forest, and SVM also demonstrate respectable accuracies ranging from 81% to 85%. While CNN falls slightly behind, it still performs reasonably well, indicating its capability in image classification tasks but perhaps lacking the complexity to match the performance of YOLOv8. KNN, Random Forest, and SVM show comparable accuracies, with Random Forest leading marginally. This suggests that ensemble methods like Random Forest can effectively harness the collective wisdom of multiple decision trees, while SVM showcases its prowess in creating optimal hyperplanes for classification.

#### 4.7 Comparative Analysis of YOLOv8 with some Existing Models

Table 3: Comparative Analysis of the Implemented and some Existing Models

S/N	Author	Algorithm	Accuracy	Key Findings
1	Li <i>et al.</i> (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 <i>et al.</i> (2023)	YOLOv3-tiny, YOLOv5s, YOLOv8n	YOLOv4, 69.40%, YOLOv7s, 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 <i>et al.</i> (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 <i>et al.</i> (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 <i>et al.</i> (2023)	P-CNN	99.75%	Developed real-time disease detection system for maize using P-CNN. Achieved 99.75% accuracy. Demonstrated faster image processing. Promising for real-time detection.
6	Implemented Model	Yolov8	99.80%	Developed a robust model with a graphical user interface for detecting maize leaf disease with an accuracy of 99.80%.

## 5. 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. Furthermore, the comparative analysis with other existing models, which shows an accuracy of 69.40% Khan *et al.* (2023) in the research work titled “Developed mobile-based system for maize disease detection integrated into mobile application for real-time detection using YOLOv3 tiny. While Bachhal *et al.* (2023) in real-time disease detection system for maize using P-CNN. Obtained a close accuracy value of 99.75%.

### 5.1 Suggestion for Future work

This research uses deep learning (Machine Language) algorithm (YOLOv8) approach for identification and prediction of maize leaf disease. Majority of similar reviewed studies adopts images of single leaves for disease detection in their research work. In respect to this, future works on maize leaf detection should be expanded to include multiple leaves in a single frame for detection of the disease. Images used for the research could be captured under different climatic environmental conditions such as temperature, humidity etc., for the purpose of decreasing their effects on disease detection. The development of new approach for maize leaf detection should be introduced considering details regarding the different stages of the disease. Furthermore, in the near future the integration of maize leaf disease detection approaches with electronic devices such as drones and mobile application should be introduced, to discover the emergence of the diseases in their early stages during crop production activities in peasant or commercial agricultural fields.

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