Harnessing the Power of Advanced Deep Learning Techniques for Early Detection and Classification of Maize Leaf Diseases in Uganda

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Abstract

Maize is a vital staple food in Uganda, eaten in various forms. However, it is often attacked by different pests and diseases that require immediate attention when detected to minimize agricultural losses. Recently, deep learning has proven to be very efficient, especially in computer vision. However, the basic model frameworks cannot efficiently capture complex image patterns. This study leverages YOLOv8 (You Only Look Once, Version 8), an advanced deep-learning model, to detect and classify maize leaf diseases using spectral maize leaf data from Uganda. The dataset comprises 37,217 maize leaf images with healthy samples and four disease classes, including Fall Army Worm (FAW), Maize Leaf Blight (MLB), Maize Lethal Necrosis (MLN), and Maize Streak Virus (MSV). Data augmentation techniques were adopted to enhance the model's robustness, including random cropping, flipping, adjustments, RGB shifts, and color jittering. Thanks to these augmentation techniques, the model's accuracy improved from 94% to 99.7%; this underscores the effectiveness of data augmentation in boosting the model's generalization ability and robustness. The model's high accuracy highlights its potential to significantly assist in early disease detection, ultimately increasing agricultural output.

Keywords: Artificial Intelligence(AI), Agriculture, Deep learning, YOLOv8, data augmentation, maize leaf diseases

1. Introduction

In Uganda, maize is a fundamental part of agriculture that supports both food security and the economy growth. Its significance extends beyond the fields, providing sustenance for communities and helping to generate income, thereby strengthening the country and fostering its prosperity. (Mugisha et al., 2011) (Mahuku et al., 2015).

Overall maize production is relatively low, and faces further setbacks due to various diseases that negatively affect crop growth and yield, these diseases include: 1. Fall Army Worm (FAW): (Hailu et al., 2018) is an insect, scientists call it Spodoptera frugiperda. This invasive species poses a significant threat to crops, particularly in Africa. Discovered in 2016, since its discovery, it has rapidly spread across many african countries, causing concern among farmers and agricultural experts. (Otim et al., 2021) Adult moths fly far, lay eggs, and eat crops. They like maize and sorghum. The larvae feed on leaves by chewing small holes in them, which creates a pattern often referred to as the" windowing" effect. This occurs because they eat the softer tissue between the veins, leaving the tougher parts intact. Additionally, the larvae also target the reproductive parts of plants, which can impact the plant's ability to produce seeds and flowers. They eat tassels (Sharon et al., 2020) cobs, and this practice leads to a decrease in the quantity of food produced by farmers. 2. Maize Leaf Blight (MLB)is a group of diseases (Adipala et al., 1993) cause by fungus Setosphaeria turcica that infect leaves, Northern corn leaf blight is one type of MLB. This fungus lives on old crops, spreads to new crops in water, (Kagoda et al., 2016) and symptoms show on leaves. The fungus grows well in warm weather, likes water. Southern corn leaf blight is another type of MLB caused by fungus Cochliobolus carbonum. It is not a big problem for farmers, however Eye spot disease and maize rust are MLBs. Mudde et al. (2018).

Maize Lethal Necrosis (MLN) is a disease that kills maize plants. This disease is caused by viruses, such as maize chlorotic mottle virus (MCMV). (Mahuku et al., 2015) It infects maize with other viruses, these viruses are in the Potyviridae family. While MCMV infection alone typically does not result in severe disease, the presence of a co-infection with another pathogen can dramatically worsen the plant's condition. This dual infection or co-infection, often leads to intensified symptoms, including substantial leaf die-off, inhibited or stunted growth, and ultimately plant mortality.

(E Isabirye and Rwomushana, 2016) The combined stress of both infections overwhelms the plant's defenses, disrupting normal growth processes and significantly reducing its chances of survival. Scientists first discover MLN in the United State of America(USA). (Fatma et al., 2016) Insects, particularly corn thrips (Frankliniella williamsi), play a major role in spreading Maize Chlorotic Mottle Virus (MCMV), which has become a significant challenge for farmers in low-income regions across Africa and Asia. These insects are highly effective at transmitting the virus, making it difficult to control the spread of the disease and affecting crop yields, especially for communities that depend on maize as a primary source of sustenance. 4. Maize Streak Virus (MSV) is a virus that leads to a disease known as maize streak disease. (Owor et al., 2007) (Emeraghi et al., 2021) This disease is characterized by the appearance of spots on the leaves of maize plants, which can stunt their growth and overall health.

The primary way this virus spreads is through leafhoppers, specifically a species called Cicadulina mbila, which acts as the main vector for transmitting the virus from one plant to another. (Gibson et al., 2005) The virus infects maize in Africa. (E Isabirye and Rwomushana, 2016) Therefore, early detection of these diseases is important to structured management-control. Despite the fact that we have developed some excellent tools to monitor plant health, many of them require time and expertise to use. (Mahuku et al., 2015) Farmers look forward to the use of automated, efficient, and accurate methods for categorizing maize leaf diseases that assist them in better informed decision making. This study based on YOLOv8(You Only Look Once, Version 8) (Li et al., 2024) (Wen et al., 2023) to create a maize leaf detector incorporating Artificial Intelligence (AI) capability to distinguish between healthy and diseased leaf by highlighting the disease infected zone in case of diseased leaves.

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The innovation of this study is not in the use of YOLOv8 alone, but how it contextualized its application and designed methodology for Ugandan agriculture. Unlike previous works which used relatively small or publicly available datasets, we created and employed a large-scale maize dataset of more than 37 thousand images captured under varied Ugandan field conditions. This variety and scale strengthens the robustness of our results and make them more reliable, also serving as a big benchmark dataset for other researchers in the future. We conducted the comprehensive analysis of YOLOv8 with competing state-of-the-art baselines (CNN, ResNet50, VGG19 and ImageNet pre-trained models) in comparative studies while many other works merely demonstrate their results alone. We make a direct connection to the urgent matter of agricultural food security in Uganda by showing how early accurate detection has potential to reduce yield loss and empower smallholder farmers. Finally, we explicitly consider how the model might be implemented in farm settings using a mobile or low-cost device in real-time as a new approach to linking theoretical research and practical application. All these components together make this work original apart from just using YOLOv8.

2. Literature Review

Deep learning has been used in many studies on plant disease detection (Li et al., 2024) (Wen et al., 2023). The integration of CNNs has become a staple in the industry because of their capability to extract spatial information from images. (Mduma and Laizer, 2023) But in terms of real-time object detection, models like YOLO (You Only Look Once) have excelled. According to this thesis (Alehegn, 2020) from Bahir Dar University in Ethiopia, that investigates the application of imaging and machine learning methods to identify and categorize diseases found on maize leaves. The thesis centers on three prevalent illnesses: Gray Leaf Spot, Common Maize Leaf Rust, and Maize Turcicum Leaf Blight. The writer gathered 800 pictures of unhealthy and healthy corn leaves and used three machine learning techniques –Kramer and Kramer (2013) KNearest Neighbor (KNN), (Zhang and Zhang, 2018) Artificial Neural Network (ANN), and (Hearst et al., 1998) (Pisner and Schnyer, 2020) Support Vector Machine (SVM) to create a detection system. Utilizing texture, color, and morphology features, the SVM algorithm achieved an accuracy rate exceeding 95%, the highest among the methods evaluated.

The thesis suggests that the created model provides a hopeful answer to improve the identification and early management of maize leaf diseases in Ethiopia. And another thesis (Maina, 2016) which was presented to Strathmore University in the year 2016 by Christine Njeri Maina. Describes a vision-centered approach for detecting maize leaf diseases in Nyeri County, Kenya, using artificial intelligence. The study focuses on the difficulties farmers encounter when trying to recognize maize diseases, specifically due to the need for visual inspection and the lack of extension workers. The thesis focuses on creating and testing a mobile app that utilizes image processing to detect diseases in maize leaves by analyzing color features and categorizing them with a neural network algorithm. And according to this research (Wen et al., 2023) from Xiaojie Wen that investigates the impact of different training methods and initial learning speeds on the ability of lightweight CNNs to identify diseases in wheat leaves. The study focuses on five specific lightweight CNN models: (Qian et al., 2021) MobileNetV3, (Ma et al., 2018) ShuffleNetV2, (Paoletti et al., 2021) GhostNet, (Wen et al., 2024) MnasNet, and (Devi et al., 2023) EfficientNetV2. The performance of these models was thoroughly examined by the researchers, who tested them with various initial learning rates and six different training strategies.

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Their findings highlight the importance of carefully selecting hyper parameters to achieve optimal model performance, ultimately identifying (Wen et al., 2024) MnasNet as the superior model for identifying wheat leaf diseases due to its high accuracy and small size. Therefore, our research work aiming to classify maize leaf images as either healthy or infected with the help of modern cutting-edge deep learning based classification techniques. We learn to detect and classify four maize leave diseases including Fall Army Worm (FAW), Maize Leaf Blight (MLB), Maize Lethal Necrosis (MLN), and Maize Streak Virus (MSV).

2.1 Proposed System

The YOLOv8 model is a new version of the classic YOLO series(Li et al., 2024)(Wen et al., 2023), that aims at better architecture to perform faster and accurate object detection.(Sohan et al., 2024) It is one of the novelty of this paper where egcocitobots are first time used for detection of agricultural diseases by involving its unique integrated Ugandan dataset, benchmark comparison against multiple deep learning architectures and situating results within the context of agricultural food security. These contributions set our work apart from previous studies on crop diseases using YOLO techniques, which were limited on scale, regional context and comparative rigor. YOLOv8 is a deep learning model, designed for real-time object detection, builds on top of previous YOLO models. Object detection finds objects in images; it then classifies them. YOLOv8 can be trained on custom datasets, which require thorough preparation, it involves selecting and labelling the objects in your training image sets. This allows you to create a custom model, that will be more accurate for a specific task. YOLOv8 has three main parts: a backbone, neck and head. The backbone extracts feature from images. It uses CSPDarknet53 as its backbone. It is the foundation of YOLOv8 model, CSPDarknet53 uses cross-stage partial connections to improve information flow between layers. The backbone can be described as a series of convolutional layers that pull pixels down to different resolutions. The neck (also known as the feature extractor) merges feature maps from different stages of the backbone, using a C2f module, (Ding et al., 2024) that combines high-level semantic features with low-level spatial information to make predictions about the objects. YOLOv8 has an anchor-free head, that predicts bounding boxes directly at the centre of objects. It has many new features, one of which is anchor-free detection. This means that, it does not use pre-defined boxes used in older models, and it is more robust and adaptable than older models. It uses a decoupled head approach; this approach is more efficient with new training tricks. One trick is stopping mosaic augmentation before the end of training. Stopping this prevents the model from overfitting, and improves accuracy. Traditional CNN models often use sliding windows for object detection. YOLOv8 treats object detection as a single regression problem. This makes it faster and reliable for several real-time object detection and classification tasks. It uses a grid-based approach to divide the input image into a grid of pixels, and then predicts bounding boxes and class probabilities for each grid cell. (Hussain et al., 2019) Traditional CNN models may not predict bounding boxes.

3. Dataset

The dataset contains images of maize leaves divided into five groups: Healthy, FAW, MLB, MLN, and MSV (O'Halloran et al., 2024). These images were gathered from different areas in Uganda to represent a variety of disease manifestations.

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Figure 1: Images illustrating leaves that are healthy.

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Figure 2: Images show leaves that have suffered fall army worm damage

Figure 3: Images show leaves affected by Maize Leaf Blight.

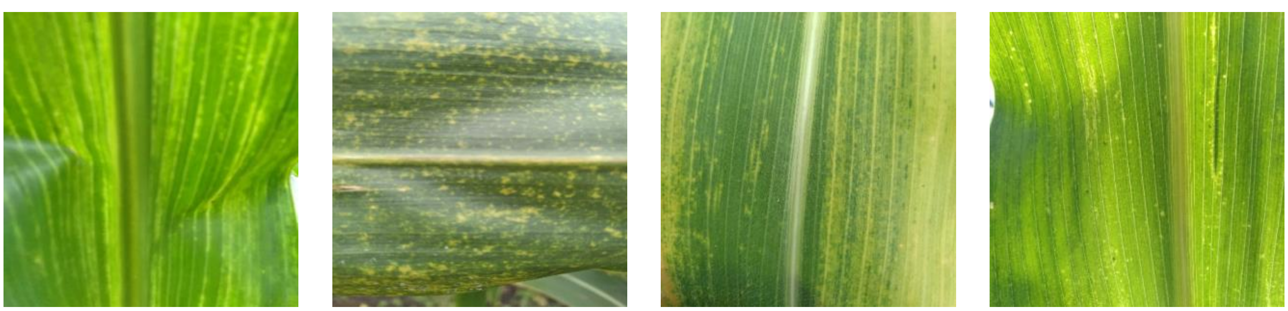

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Figure 4: MLN - Images show leaves affected by Maize Lethal Necrosis

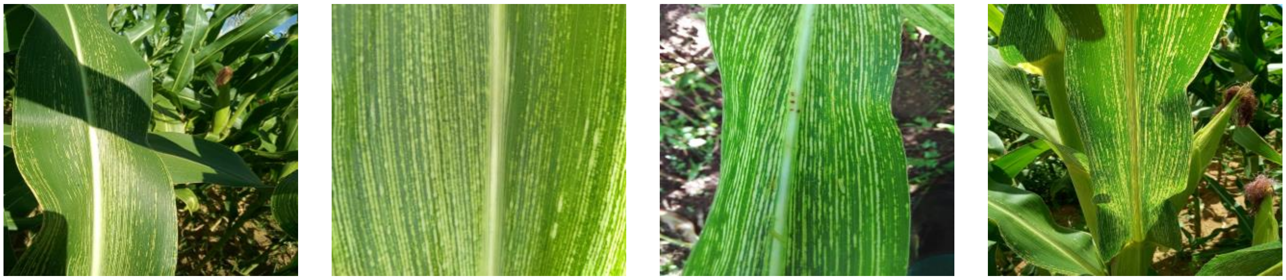

Figure 5: MSV - Images show leaves affected by Maize Streak Virus.

3.1 Data Preprocessing

The pictures were adjusted to 640x640 pixels, to fit YOLOv8 input size (Shorten and Khoshgoftaar, 2019) (Mikol ajczyk and Grochowski, 2018). Various data augmentation methods, like rotation, flipping and scaling were used to expand the dataset and add diversity. (Perez and Wang, 2017)

For each image $I \in$ images path

Read image I

For x = 1 to 2:

$I' \leftarrow$ RandomCrop (I, width = 640, height = 640, p = 1)

$I' \leftarrow$ Horizontal Flip (I', p = 0.4)

$I' \leftarrow$ RandomGamma (I', p = 0.2)

$I' \leftarrow$ RGBShift (I', p = 0.2)

$I' \leftarrow$ VerticalFlip (I', p = 0.2)

$I' \leftarrow$ Color Jitter (I', contrast = 0, saturation = 0.1, hue = 0.015, brightness = 0.4) Save I' as image name x .jpg

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4. Model Architecture

The YOLOv8 model is made up of layers of convolutions along, with fully connected layers. (Tyagi et al.) It employs a network to forecast both bounding boxes and class probabilities at the same time. (Sohan et al., 2024) The detailed design of the architecture is depicted in Figure 6 below.

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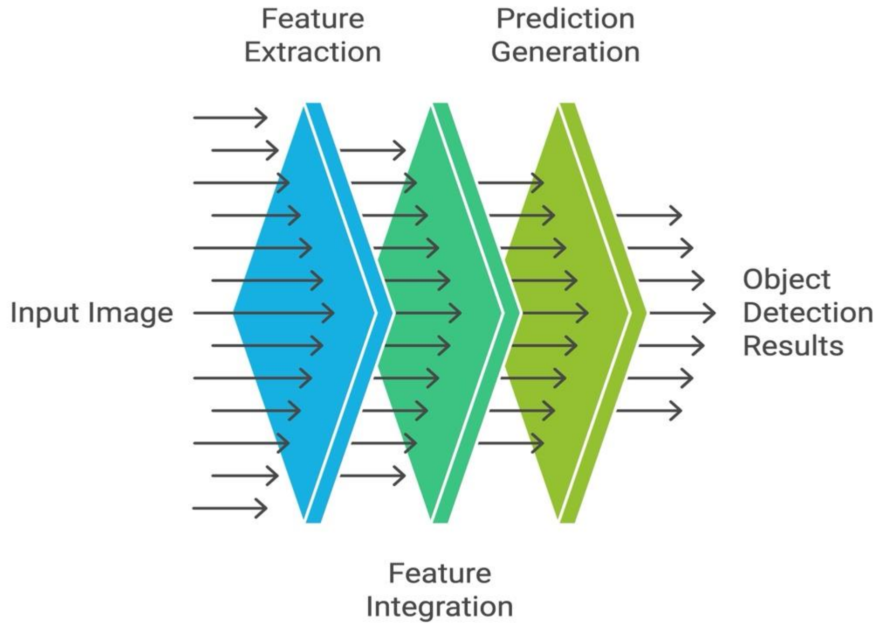

Figure 6: YOLOv8-large Model Architecture

YOLOv8-large Model Architecture used for this research project is made up of backbone, neck, and head which are crucial for object detection and classification. The backbone processes information from the input image. It is made up of convolutional layers that decrease the size of the spatial dimensions while increasing the thickness of the feature maps. The spine frequently employs architectures such as CSPNet or ResNet to extract features effectively. This method enables the model to capture significant visual data across various scales. The neck links the spine to the head. It combines feature maps from various layers, enabling the model to utilize both detailed and general features. This stage is essential to enhance the precision of detection, particularly for objects of different sizes. The neck usually utilizes systems such as Feature Pyramid Networks (FPN) or PANet to help in this merging procedure. Predictions are created by the head using information processed by the backbone and neck. It generates boxes that bound objects, scores for the object's class, and scores for the object's presence. The leader has the ability to utilize different loss functions in order to improve detection performance. This phase transforms the acquired characteristics into practical results that can be applied to activities such as categorization and pinpointing. All components of the YOLOv8 model collaborate to improve the efficiency and accuracy of object detection. Comprehending these elements can assist in fine-tuning and customizing the model for particular use.

4.1 Training

This model was trained using supervised learning approach. The loss was the sum of localization, confidence and classification losses as written below:

$$L = L_{loc} + L_{conf} + L_{cls} \quad (1)$$

where L_{loc} is the localization loss, L_{conf} is the confidence loss, and L_{cls} is the classification loss. (Zhang, 2018) Adam optimizer was employed with a learning rate of 0.01. Trainings were made for 100 epochs, one epoch represented by a single pass of all dataset through it at once.

Table 1: Images used for Training the YOLOV8-large model

Class	Collected Images	After Data Augmentation
Healthy	9,132	10,000
FAW	935	10,000
MLB	3,695	10,000
MLN	2,786	10,000
MSV	9,515	10,000

Table 2: Images used for Validating the YOLOV8-large model

Class	Collected Images	After Data Augmentation
Healthy	2,609	5,000
FAW	267	5,000
MLB	1,055	5,000
MLN	796	5,000
MSV	2,718	5,000

Table 3: Images used for Testing the YOLOV8-large model

Class	Collected Images
All	3,729

4.2 Evaluation

The model's performance was evaluated using precision, recall, F1-score, and mean Average Precision (mAP). (Heydarian et al., 2022) (Caelen, 2017) A confusion matrix was also generated to visualize the classification results. The AP provides a measure of quality across all recall levels for single class classification, it can be seen as the area under the precision-recall curve. Then the mAP is the mean of APs in multi-class classification. Precision represents the ratio of correctly classified positive examples to the total classified positive examples, assessing the model's accuracy. Meanwhile, Recall measures the number of correctly identified positive examples out of all actual positive examples, gauging the model's effectiveness in capturing all positives within the dataset. (Cabral et al., 2011) F1 score computes the average of precision and recall, where the relative contribution of both of these metrics are equal to F1 score.The best value of F1 score is 1 and the worst is 0. What does this mean? This means a perfect model will have a F1 score of 1 – all of the predictions were correct.

$$\text{mAP} = \frac{1}{N}\sum_{i=1}^{N}\frac{TP_i}{TP_i + FP_i} \quad (2)$$

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$$\text{Precision} = \frac{TP}{TP+FP} \qquad (3)$$

$$\text{Recall} = \frac{TP}{TP+FN} \qquad (4)$$

F1 score =2(precision X Recall)/ (Precision + Recall) (5)

Where: N is the number of detection sample categories; TP is the number of real positive samples (the number of positive samples detected as positive samples), which is measured by the number of detection frames with IoU is greater than 0.5, that is, the number of correct detections; FP is the number of false positive samples (the number of negative samples that are detected as positive samples), which is measured by the detection box of IoU less or equal to 0.5, that is, the number of detection errors; FN is the number of false negative samples (the number of positive samples that are detected as negative samples).

4.3 Model Performance

The YOLOv8 model achieved a F1 score and mAP of 99.7% after data augmentation, demonstrating high accuracy in classifying maize leaf diseases, however, we trained multiple deep learning models and evaluated their performance.

The precision, recall, F1-score, and mean absolute precision(mAP) for each model are detailed in Table 4 and 5. YOLOv8 achieved better precision, recall, F1-score and mean Average Precision (mAP) than CNN, VGG19, ResNet50 and ImageNet. This improvement in performance is mainly attributed to the architectural advances of YOLOv8, for instance CSPDarknet53 backbone, C2f neck for fusing multi-scale features and anchor-free detection head. In contrast, traditional CNNs only had weak generalisations, particularly when dealing with complex background noise as commonly appears in agricultural images. VGG19 and ResNet50 did comparably well but with the drawback of higher computational resources requirement and slower inference speed thus less ideal for real-time agricultural applications.

A key observation is that, even though ImageNet and VGG19 have got relatively high recalls but their low precisions resulted in a large number of false positive- not suitable to farmers who demand accurate detection. While the developed YOLOv8 in comparison reported near-perfect precision (0.999 after augmentation), reducing incorrect classifications for trusted decision support during field application. A practical consequence of this is that farmers can trust YOLOv8's predictions with no expert validation, saving time to intervention.

Table 4: Collected Data

Model	Precision	Recall	F1-score	mAP
YOLOv8	0.93	0.97	0.94	0.95
CNN	0.88	0.796	0.835	0.87
VGG19	0.915	0.90	0.907	0.90
ResNet50	0.902	0.88	0.89	0.89
ImageNet	0.897	0.88	0.888	0.90

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Table 5: After Data Augmentation

Model	Precision	Recall	F1-score	mAP
YOLOv8	0.999	0.995	0.997	0.997
CNN	0.904	0.896	0.90	0.90
VGG19	0.97	0.951	0.96	0.97
ResNet50	0.941	0.90	0.92	0.92
ImageNet	0.91	0.96	0.93	0.914

4.4 Confusion Matrix

The confusion matrix indicates the number of correct and incorrect classifications for each class predicted by yolov8 model.

Table 6: Collected Images (F1 Score: 94%)

	Healthy	FAW	MLB	MLN	MSV
Healthy	9000	100	20	10	2
FAW	20	900	5	5	5
MLB	30	10	3650	0	5
MLN	5	5	0	2770	6
MSV	40	5	5	5	9480

Table 7: After Data Augmentation (F1 Score: 99.7%)

	Healthy	FAW	MLB	MLN	MSV
Healthy	9980	5	5	5	5
FAW	5	9995	0	0	0
MLB	0	0	9995	0	5
MLN	5	0	0	9990	5
MSV	10	0	0	0	9990

4.5 Graphical Representation

The figure 7 shows the yolov8 model's validation accuracy trends over the training epochs, indicating convergence and stability.

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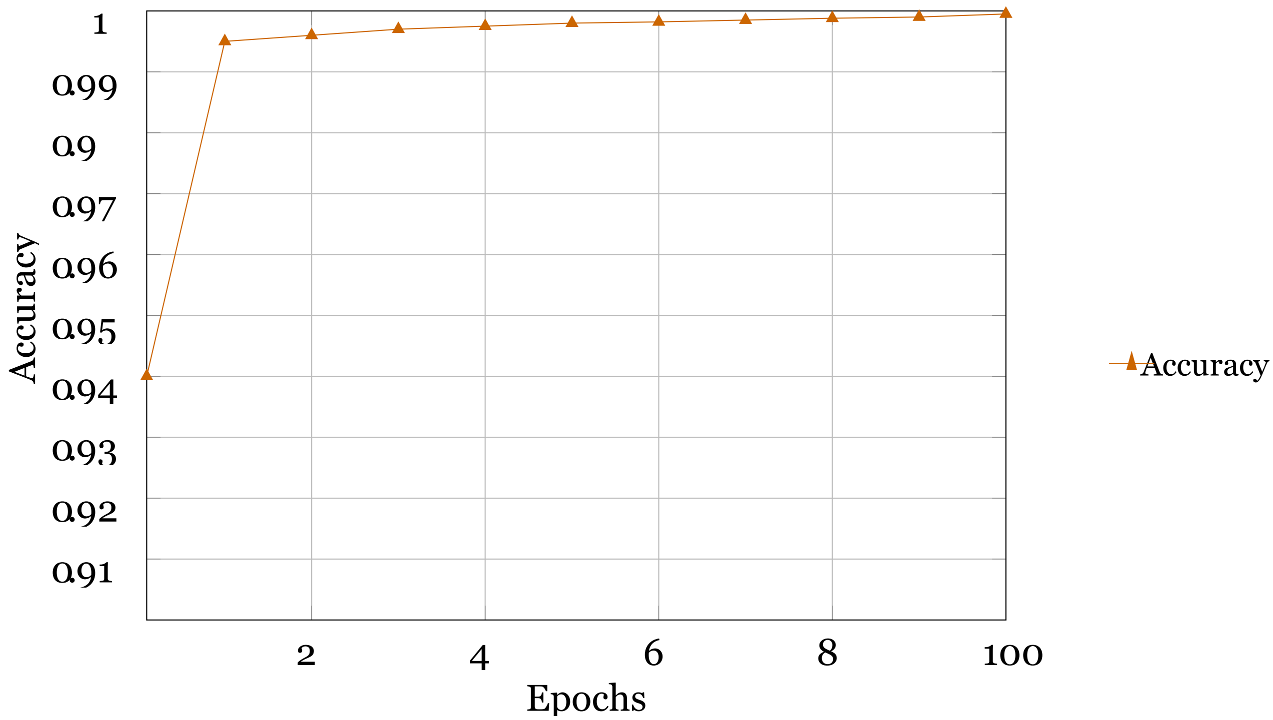

Figure 7: Validation Accuracy vs Epochs

5. Analysis

The YOLOv8 model performed superbly in detecting diseases. The results point out that it is capable of dealing with the fluctuation and convolutions of the disease symptoms in maize leaves. This study discusses how we apply modern technological classification techniques by the YOLOv8 model to classify maize leaf images as either healthy or diseased. This study, in fact, plays a vital role in the following areas:

Addressing a Critical Need in Ugandan Agriculture

1. Food Security: Maize, being the key food crop in Uganda is both important in providing food and maintaining the country's economy. Diseases like Fall Army Worm(FAW)(Hailu et al., 2018), Maize Leaf Blight (MLB)(Kagoda et al., 2016), Maize Lethal Necrosis (MLN)(Mahuku et al., 2015)(E Isabirye and Rwomushana, 2016) and (Emeraghi et al., 2021) Maize Streak Virus (MSV) seriously damage maize crops. Early and correct detection of these diseases can stop huge loss in crops and consequently ensuring food availability and stability in the country.

2. Economic Impact: The reduction of the disease outbreaks could help farmer shave a surplus of suppliers along with the production of highquality agricultural products. This is a win-win situation; hence, it will result in the farmers' increased income and, subsequently, improvement in their livelihood. This has a positive effect on the local economy, which is the primary source of employment and revenue in Uganda.

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Technological Advancements in Disease Detection

1. Cutting-Edge Technology: the implementation of YOLOv8 model real time object detection and classification, is a major boost to agricultural technology. The model has capabilities like classifying and isolating disease infested areas on maize leaves, hence, has become more than powerful for the farmers and agricultural professionals.
2. Data-Driven Decision Making: the application of modern deep learning techniques ensures that specific and reliable detection and classification of disease takes place. This will help farmers to be in charge of their farms by making informed decisions about the management of disease and intervention strategies, hence improving health and productivity of crops.

Practical Applications and Broader Implications

1. Scalability and Adaptability: the methodologies and findings from this research can be adapted in order to solve crops problem, in other geographical regions. This makes it highly valuable, as similar techniques can be implemented to take measures about agricultural challenges worldwide.
2. Integration with E-Health Solutions: This model has potential to be integrated into e-health solutions and can offer farmers a tool for fast, real-time disease diagnostics. The possibility of wide spread technology revolution is achieved by the fact that opens up advanced technology to low income farmers who previously could not access such gadgets.
3. Promoting Sustainable Agriculture: Quick detection and accurate classification of diseases lead to specific interventions, thus, there is no need for general application of pesticides. This results in the application of more sustainable practices in farming by minimizing the environmental impact and improving safety of agricultural products.

5.1 Implications

The model can be an irreplaceable tool to farmers in Uganda. By enabling early detection and control of diseases by means of structured prototype the model provides a unique service that is undoubtedly superior to the current approach, and therefore, it may help farmers to achieve more stable and higher yields and food security.

6 Conclusion

This study successfully demonstrated the efficacy of advanced deep learning techniques, specifically the YOLOv8 model, for early detection and classification of maize leaf diseases in Uganda. By utilizing a robust dataset of 37,217 maize leaf images and implementing various data augmentation techniques, the model achieved an impressive accuracy of 99.7%. This significant enhancement underscores the model’s potential to provide timely and accurate disease identification, which is crucial for mitigating agricultural losses and improving maize production. The findings highlight the importance of leveraging artificial intelligence in agriculture to support farmers in making informed decisions and optimizing crop health management.

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6.1 Future Work

Future research should focus on expanding the dataset to include more diverse images from different regions and conditions to enhance the model's generalization capabilities; the experiments would be even more robust in application of the model to real farm conditions with variations in lighting, background clutter, leaf overlaps and dust is therefore yet to be extensively tested. Additionally, exploring the integration of other machine learning algorithms and hybrid models could provide comparative insights and further improve detection accuracy. Real-time application of the model via mobile or web-based platforms could also be investigated, enabling farmers to access disease detection tools easily. Furthermore, ongoing studies on the impact of detected diseases on yield loss and developing decision-support systems based on model predictions will be critical in translating these technological advancements into practical agricultural solutions.

7 Appendix

Table 8: Mathematical Notations

Notation	Definition
L	Total loss
L_{loc}	Localization loss
L_{conf}	Confidence loss
L_{cls}	Classification loss
λ	Regularization parameter
∑	Summation of all classes

7.1 Problem Solved

Maize is a staple food crop in many parts of the world, especially in Africa. The primary objective was to create a machine learning model to classify maize leaves as healthy or diseased (FAW, MLB, MLN, or MSV). This model assists farmers and agricultural experts in early disease detection, enabling timely intervention and treatment. The project addresses the need for an automated, reliable, and accessible solution for identifying maize leaf diseases, benefiting Ugandan farmers.

7.2. Framework Used in This Study

Several machine learning frameworks were explored, including CNN and VGG19, with YOLOv8 chosen as the best-performing model due to its superior accuracy and efficiency. The project involved key steps, as follows:

73. Challenges Faced and Solutions

The project encountered several challenges: Time and Resource Constraints: Training deep learning models with large datasets required significant computational resources. High-performance computing resources were utilized to mitigate these constraints. Model Selection and Fine-Tuning: Selecting and tuning the optimal model was complex. However, Systematic experimentation with frameworks and hyper parameters led to selecting YOLOv8 as the best-performing model. Data Augmentation: Ensuring the augmented dataset remained representative without introducing noise. Therefore, Careful application of augmentation techniques preserved the dataset's integrity.

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7.4. Outcomes and Achievements

This research work achieved an accuracy of 99.7%, up from an initial 94%. Data augmentation contributed to this improvement, enhancing model robustness and performance.

- **Accuracy Improvement**: The final model accuracy improved from 94% to 99.7%.
- **Dataset Expansion**: The dataset expanded from 26,043 to 50,000 images, increasing model training data and performance.

7.5 Resources Used

This study leveraged various resources:

- **Programming Language**: Python
- **Frameworks and Libraries**: YOLOv8, CNN, VGG19, Augmentations (for data augmentation)

References

Adipala, PE Lipps, and LV Madden. Reaction of maize cultivars from uganda to exserohilum turcicum. Phytopathology, 83(2):271–223, 1993.

Ambrose Agona, Jane Nabawanuka, and H Muyinza. An overview of maize in uganda. Post-harvest Programme, NARO Uganda, 2001.

Enquhone Alehegn. Maize Leaf Diseases Recognition and Classifiaction Based on Imaging and Machine Learning Techniques. PhD thesis, 2020.

Ricardo Cabral, Fernando Torre, Joao P Costeira, and Alexandre Bernardino. Matrix completion for multi-label image classification. Advances in neural information processing systems, 24, 2011.

Olivier Caelen. A bayesian interpretation of the confusion matrix. Annals of Mathematics and Artificial Intelligence, 81(3):429–450, 2017.

RS Devi, VR Kumar, and P Sivakumar. Efficientnetv2 model for plant disease classification and pest recognition. Computer Systems Science & Engineering, 45(2), 2023.

Weiping Ding, Xiaotian Cheng, Yu Geng, Jiashuang Huang, and Hengrong Ju. C2f-explainer: Explaining transformers better through a coarse-to-fine strategy. IEEE Transactions on Knowledge and Data Engineering, 2024.

Brian E Isabirye and Ivan Rwomushana. Current and future potential distribution of maize chlorotic mottle virus and risk of maize lethal necrosis disease in africa. Journal of crop protection, 5(2):215–228, 2016.

Mary Emeraghi, Enoch G Achigan-Dako, Chibuzo NC Nwaoguala, and Happiness Oselebe. Maize streak virus research in africa: an end or a crossroad. Theoretical and Applied Genetics, 134(12):3785–3803, 2021.

IJBEST ISSN (2959-586X) and ISBN (978-9970-9943-4-2)

Hussein Kiruwa Fatma, Feyissa Tileye, and Alois Ndakidemi Patrick. Insights of maize lethal necrotic disease: A major constraint to maize production in east africa. African Journal of Microbiology Research, 10(9):271–279, 2016.

RW Gibson, NG Lyimo, AEM Temu, TE Stathers, WW Page, LTH Nsemwa, G Acola, and RI Lamboll. Maize seed selection by east african smallholder farmers and resistance to maize streak virus. Annals of applied biology, 147 (2):153–159, 2005.

Girma Hailu, Saliou Niassy, Khan R Zeyaur, Nathan Ochatum, and Sevgan Subramanian. Maize–legume intercropping and push–pull for management of fall armyworm, stemborers, and striga in uganda. Agronomy Journal, 110(6): 2513–2522, 2018.

Marti A. Hearst, Susan T Dumais, Edgar Osuna, John Platt, and Bernhard Scholkopf. Support vector machines. IEEE Intelligent Systems and their applications, 13(4):18–28, 1998.

Mohammadreza Heydarian, Thomas E Doyle, and Reza Samavi. Mlcm: Multilabel confusion matrix. IEEE Access, 10:19083–19095, 2022.

Mahbub Hussain, Jordan J Bird, and Diego R Faria. A study on cnn transfer learning for image classification. In Advances in Computational Intelligence Systems: Contributions Presented at the 18th UK Workshop on Computational Intelligence, September 5-7, 2018, Nottingham, UK, pages 191–202. Springer, 2019.

Frank Kagoda, Robert Gidoi, and Brian E Isabirye. Status of maize lethal necrosis in eastern uganda. African Journal of Agricultural Research, 11(8): 652–660, 2016.

Oliver Kramer and Oliver Kramer. K-nearest neighbors. Dimensionality reduction with unsupervised nearest neighbors, pages 13–23, 2013.

Rujia Li, Yadong Li, Weibo Qin, Arzlan Abbas, Shuang Li, Rongbiao Ji, Yehui Wu, Yiting He, and Jianping Yang. Lightweight network for corn leaf disease identification based on improved yolo v8s. Agriculture, 14(2):220, 2024.

Ningning Ma, Xiangyu Zhang, Hai-Tao Zheng, and Jian Sun. Shufflenet v2: Practical guidelines for efficient cnn architecture design. In Proceedings of the European conference on computer vision (ECCV), pages 116–131, 2018.

George Mahuku, Benham E Lockhart, Bramwel Wanjala, Mark W Jones, Janet Njeri Kimunye, Lucy R Stewart, Bryan J Cassone, Subramanian Sevgan, Johnson O Nyasani, Elizabeth Kusia, et al. Maize lethal necrosis (mln), an emerging threat to maize-based food security in sub-saharan africa. Phytopathology, 105(7):956–965, 2015.

Christine Njeri Maina. Vision-based model for maize leaf disease identification: a case study in Nyeri County. PhD thesis, Strathmore University, 2016.

Neema Mduma and Hudson Laizer. Machine learning imagery dataset for maize crop: a case of tanzania. Data in Brief, 48:109108, 2023.

Agnieszka Mikol ajczyk and Michal Grochowski. Data augmentation for improving deep learning in image classification problem. In 2018 international interdisciplinary PhD workshop (IIPhDW), pages 117–122. IEEE, 2018.

Barnabas Mudde, Florence Olubayo, Douglas Watuku Miano, Godfrey Asea, Dora C Kilalo, Andrew Kiggundu, Daniel K Bomet, and John Adriko. Distribution, incidence and severity of maize lethal necrosis disease in major maize growing agro-ecological zones of uganda. Journal of Agricultural Science, 10 (6):72, 2018.

Johnny Mugisha, Gratious M Diiro, William Ekere, AS Langyintuo, and WM Mwangi. Characterization of maize producing households in nakasongola and soroti districts in uganda. 2011.

Michael Hilary Otim, Stella Adumo Aropet, Moses Opio, Dalton Kanyesigye, Henry Nakelet Opolot, and Wee Tek Tay. Parasitoid distribution and parasitism of the fall armyworm spodoptera frugiperda (lepidoptera: Noctuidae) in different maize producing regions of uganda. Insects, 12(2):121, 2021.

Betty E Owor, Darren P Martin, Dionne N Shepherd, Richard Edema, Aderito L Monjane, Edward P Rybicki, Jennifer A Thomson, and Arvind Varsani. Genetic analysis of maize streak virus isolates from uganda reveals widespread distribution of a recombinant variant. Journal of general virology, 88(11): 3154–3165, 2007.

Tony O'Halloran, George Obaido, Bunmi Otegbade, and Ibomoiye Domor Mienye. A deep learning approach for maize lethal necrosis and maize streak virus disease detection. Machine Learning with Applications, 16:100556, 2024.

Mercedes E Paoletti, Juan M Haut, Nuno S Pereira, Javier Plaza, and Antonio Plaza. Ghostnet for hyperspectral image classification. IEEE Transactions on Geoscience and Remote Sensing, 59(12):10378–10393, 2021.

Buteme Sharon, Masanza Michael, and Masika Fred Bwayo. Severity and prevalence of the destructive fall armyworm on maize in uganda: A case of bulambuli district. African Journal of Agricultural Research, 16(6):777–784, 2020.

Xiaojie Wen, Minghao Zeng, Jing Chen, Muzaipaer Maimaiti, and Qi Liu. Recognition of wheat leaf diseases using lightweight convolutional neural networks against complex backgrounds. Life, 13(11):2125, 2023.

Xiaojie Wen, Muzaipaer Maimaiti, Qi Liu, Fusheng Yu, Haifeng Gao, Guangkuo Li, and Jing Chen. Mnasnet-simam: An improved deep learning model for the identification of common wheat diseases in complex real-field environments. Plants, 13(16):2334, 2024.

Zhihua Zhang and Zhihua Zhang. Artificial neural network. Multivariate time series analysis in climate and environmental research, pages 1–35, 2018.

Zijun Zhang. Improved adam optimizer for deep neural networks. In 2018 IEEE/ACM 26th international symposium on quality of service (IWQoS), pages 1–2. IEEE, 2018.