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Sugarcane And Mango Leaf Disease Detection Using Data Augmentation And Yolov8

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Abstract: *The identification of crop diseases is essential for sustainable agricultural practices and preservation of farm income. This research emphasizes the detection of diseases in sugarcane and mango leaves using contemporary object detection methods and augmentation strategies. These two crops are known to suffer from diseases that can cause economic losses if left unmitigated, so early detection and diagnosis is needed for effective disease control. For this study, the YOLOv8 model was selected as it has high detection accuracy, runs in real-time, and can detect multiple diseases from the same image. Through the application of extensive data augmentation, such as flipping, rotation, scaling, and addition of noise, we modeled the YOLOv8 process to make it as generalizable, robust, and reliable as possible. Applying augmentation increases diversity in the dataset, but also helps combat overfitting when developing the model, which ultimately enhances the model's predictive ability on previously unseen data. We selected the augmented dataset and trained it on the YOLOv8 model and analyzed performance metrics including mean Average Precision (map), Precision, Recall, and F1-measure. The results prove that YOLOv8, in conjunction with augmentation can achieve very high levels of detection accuracy, and highlighted the increased effectiveness of being able to note diseased areas better than previous models. This work provides an example of the evolving nature of artificial intelligence and its impact in a rapidly changing agricultural world, and supports a vision of a day when drone or imaging technologies could be practically adopted for use in agriculture.*

Keywords: *Sugarcane, Mango Leaves, Disease Detection, YOLOv8, Data Augmentation, Agriculture, Deep Learning, Object Detection.*

1.INTRODUCTION AND OVERVIEW

1.1Overview of Agricultural Diseases and Their Impact on Yield

Agricultural diseases significantly threaten global food security, causing substantial economic losses and reduced crop productivity. Sugarcane and mango leaves are particularly vulnerable to various diseases, including fungal, bacterial, and viral infections [1]. Infected crops often exhibit symptoms like leaf spots, discoloration, and premature leaf drop, which directly affect photosynthesis and overall plant health. If not detected and managed promptly, these diseases can lead to significant yield reductions and economic hardships for farmers, impacting both local and international markets.[2]

1.2 Importance of Early Detection in Sugarcane and Mango Leaves

The early detection of diseases in sugarcane and mango leaves is essential for effective disease management. Timely identification allows farmers to apply targeted treatments, reducing the spread of infections and minimizing crop damage [1]. Early detection not only improves yield quality and quantity but also reduces dependency on extensive chemical usage, which can harm the environment. Implementing automated disease detection systems can significantly enhance the efficiency of monitoring large agricultural fields, enabling proactive interventions.[3]

1.3Introduction to YOLOv8 and Its Advantages

YOLOv8 (You Only Look Once, version 8) is a leading-edge object detection algorithm, known for its real-time performance and accuracy [4] while incorporating advanced features like further backbone architecture improvements or feature fusion methods to improve performance. It also provides an advantage for agricultural applications by processing more complex images containing multiple objects and different backgrounds compared to its predecessors. Overall, YOLOv8 shows an increase in speed, accuracy, and computational efficiency which make it suitable for a real-time detection of disease in sugarcane and mango crops.[5]

1.4 Objectives of the Research

To develop an efficient model for detecting diseases in sugarcane and mango leaves.

To utilize data augmentation techniques to enhance model robustness and accuracy.

To evaluate YOLOv8's performance in identifying diseased and healthy leaves.

2. RELATED WORK

2.1 A Lightweight YOLOv8 based on attention mechanism for mango pest and disease detection.

In this study, the GAS-YOLOv8 lightweight target detection model was proposed and tested on 10 pests and three diseases of mangoes. By comparing the YOLOv8n and GAS-YOLOv8 models, it was concluded that the GAS-YOLOv8 model has advantages and greater potential for development in the lightweight detection of mango pests and diseases. Among these indicators, the mAP50 for mango pests reached 98.6%, the mAP50 for diseases reached 91.7%, and the number of parameters decreased by 33%.

2.2 Deep learning-based mango leaf disease detection for classifying and evaluating mango leaf diseases.

The evaluation of deep learning models for mango leaf disease detection revealed valuable insights, indicating their potential applicability in agricultural settings experiments and analysis, with YOLOv8 with African Buffalo Optimization emerging as the top-performing model with the highest classification accuracy at 94.5%.Furthermore, from the comparative analysis, YOLOv8, GoogLeNet, VGG16, MobileNet and EfficientNet showed relatively high performance with accuracies of 92.7%, 90.7%, 88.0% and 90% respectively.

2.3 An improved YOLOv8 model for accurate identification sugarcane seed sprouts.

This study established a sugarcane seed sprout dataset and made several improvements to the basic model of YOLOv8s. As a result, the improved sugarcane-YOLO model achieved an accuracy of 97.42%, a recall rate of 98.63%, and mAP50, mAP75, and mAP50-95 values of 99.05, 81.3 and 71.61%, respectively.

3. FORMULATION AND FRAMEWORK

3.1 Challenges in Detecting Sugarcane and Mango Leaf Diseases:

Variability in Symptoms: Diseases manifest differently depending on the type, severity, and environmental conditions, leading to high infraclass variability.

Complicated Backgrounds: Leaf images often include complicated and distracting backgrounds that hide leaf features, making segmentation and detection difficult.

Limited Datasets: It is difficult to obtain large datasets of diseased leaves for certain diseases because a large amount of disease data is only available only for part of the year, and in some regions.

Real-Time Requirement: Agricultural monitoring systems use real-time detection so that they can take immediate action and intervention also using efficient models.

Scalability: The solution must scale to vast fields, handling different crops, diseases, and image qualities effectively.

3.2 Proposed Solution with a Conceptual Framework

The proposed solution integrates YOLOv8 with data augmentation techniques to address the challenges in detecting sugarcane and mango leaf diseases. The framework comprises the following stages:

Data Acquisition: Collecting high-quality images of sugarcane and mango leaves from diverse sources, covering various disease types and healthy samples.

Data Augmentation: Applying transformations such as rotation, flipping, noise addition, and scaling to increase dataset diversity.

Model Training: Training YOLOv8 using the augmented dataset, leveraging its efficient architecture for real-time object detection.

Evaluation: Using metrics such as mean Average Precision(map), Precision, and Recall to validate model performance.

Deployment: Deploying the trained model in field monitoring systems or drone-based solutions for real-time disease detection.

3.4 Justification for Selecting YOLOv8 and Data Augmentation

YOLOv8 is selected for its ability to detect objects with high precision and speed, making it ideal for agricultural applications requiring real-time analysis. Its improved architecture enables better feature extraction and robustness against complex backgrounds. Data augmentation complements YOLOv8 by addressing dataset limitations, enhancing the model's ability to generalize to unseen data and varying environmental conditions.

3.4.1 Key Formula

The YOLOv8 loss function, which guides model

optimization, is defined as:

$$\mathcal{L}{total} =\mathcal{L}{box} +\mathcal{L}{obj} +\mathcal{L}{cls}$$

Eq.1 : YOLOV8 Loss function

Eq (1): Loss Function for yolo object detection model

This Equation1 helps us knowing the loss function of the YOLOV8, which includes localization loss, objectness loss, classification loss.

Where :

{L}{box} = Bounding box regression loss

{L}{obj} = Objectness loss

{L}{cls}= Classification loss

3.4.2Framework

Framework for detecting disease for sugarcane

and mango leaves can be visualized as follows:

1. **Input:** Images of sugarcane and mango leaves.
2. **Preprocessing:** Data augmentation.
3. **Model Training:** YOLOv8-based architecture.
4. **Output:** Disease localization and classification.

4. METHODOLOGY

4.1Data Collection

The dataset for this exploration comprises images of sugarcane and mango leaves collected from different sources

Field Images Photos taken directly from agrarian fields using high-resolution cameras to capture natural conditions, including variations in lighting, angles, and backgrounds.

Public Datasets Being datasets from depositories like Plant Village and Kaggle were employed to condense field images.

The dataset includes both healthy and diseased samples. For sugarcane leaves, conditions similar as rust, red spoilage, and splint scald are considered. For mango leaves, common conditions like anthracite, fine mildew, and bacterial black spot are included. Each image is labeled with bounding boxes indicating complaint-affected areas, enabling supervised literacy. This dataset is split into two subsets like 80% for training and 20% for testing.

4.2Data Augmentation and addition strategies

To improve the robustness and generalization here a series of augmentation techniques were applied to the training set. which includes:

Flipping Vertical and perpendicular flips to pretend to vary splint exposures.

Rotation Random reels (e.g., ± 20 °) to mimic different camera angles.

Spanning Random drone-heft and drone- eschewed operations to pretend varied distances.

Noise Addition Gaussian noise to pretend environmental conditions and ameliorate model robustness.

These ways enhance dataset diversity, precluding overfitting and perfecting conception to unseen data.

4.3 Data Preprocessing

Such augmentations not only increased the size of the dataset, but represented variability in how the leaf appears in the real world when the lighting changes, whether the plant is oriented differently, and when the background is different. These variations in the lighting, orientation, and background of the plants when being surveyed and detecting are important factors to increase detection accuracy in real-world agricultural scenarios.

The model was trained for 100 epochs using the Adam optimizer with a learning rate of 0.001, a batch size of 32, and a cross-entropy based object detection loss function. All experiments were completed in the PyTorch deep learning framework, using OpenCV for data preprocessing. For training and inference, CUDA speed up using a GPU was very useful as deep learning requires a lot of computational resources.

4.4Model perpetration

4.4.1 Architecture and Features

YOLOv8 employs an advanced backbone armature with bettered point birth capabilities and effective point emulsion mechanisms. Its crucial features include Anchor-Free Discovery Simplifies bounding box retrogression.

Dynamic point Fusion Better integration of spatial and contextual information.

YOLOv4

YOLOv4 (You Only Look Once version 4) is a real-time object detection model presented to enhance the performance of earlier YOLO versions by achieving a balance between speed and accuracy. YOLOv4 is designed for training and deployment on common GPU hardware, which makes it available for wider research and real-world use.

YOLOv4 employs CSPDarknet53 as the backbone, which improves learning ability by Cross-Stage Partial connections. Spatial Pyramid Pooling (SPP) and Path Aggregation Network (PANet) are used in the neck to enhance receptive field and semantic information transmission. Bag-of-freebies (e.g., data augmentation methods like Mosaic and Drop Block regularization) and bag-of-specials (e.g., Mish activation and CIoU loss) are employed to further enhance the robustness of the model without additional inference cost.

YOLOV5

YOLOv5 (You Only Look Once version 5) is a real-time object detection model by Ultralytics, which is extremely fast, accurate, and deployable. It is segregated into three primary components: the backbone, neck, and head. The backbone, usually CSPDarknet53, extracts feature from input images through convolutional layers, residual blocks, and SiLU activation functions. The neck utilizes Feature Pyramid Networks (FPN) and Path Aggregation Networks (PAN) to aggregate features across various layers, enhancing multi-scale object detection. The head predicts bounding boxes, objectness scores, and class probabilities at three scales (small, medium, large) for strong multi-scale detection.

YOLOv5 employs anchor-based detection and allows automatic anchor learning during training. It is both speed- and accuracy-optimized, providing lightweight variants (YOLOv5n, s, m, l, x) to cater to differing resource and performance requirements. New features include support for multiple export formats (such as ONNX, CoreML, TensorRT), data augmentation methods like Mosaic and MixUp, and the use of CIoU loss for more accurate bounding box regression. Its simplicity, its ability to support transfer learning, and its great inference speed make YOLOv5 a popular model for most real-time computer vision applications.

YOLOV8

YOLOv8 (You Only Look Once, v8) is the newest object detection and vision model from Ultralytics. It is a monumental leap from the older versions of YOLO like YOLOv5 and YOLOv7. In contrast to previous YOLO models that normally used anchor-based detection and depended on CSPDarknet backbones, YOLOv8 is a completely redesigned architecture that is anchor-free, light, and modular, supporting not just object detection but also tasks like image classification, instance segmentation, pose estimation, and object tracking. With advancements in both architectural performance and learning procedures, YOLOv8 demonstrates state-of-the-art results on a diverse set of benchmarks while sustaining fast inference speeds applicable for real-time applications.

The YOLOv8 architecture can be divided into three main components: the Backbone, Neck, and Head, which serve different purposes in the visual information processing pipeline.

Backbone

The backbone performs the task of extracting hierarchical feature representations from the input image. YOLOv8 employs a custom-developed CNN backbone with C2f (Cross-Stage Partial Fusion) modules, which are an improvement over CSP (Cross-Stage Partial) layers that were employed in YOLOv5. The C2f modules enhance gradient flow and computational efficiency by backpropagating partial feature maps using skip connections.

Neck

The neck combines and fuses features from various spatial resolutions to facilitate multi-scale object detection. YOLOv8 maintains the Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) hybrid architecture that was initially introduced in YOLOv5. This architecture enables the model to pass low-level fine-grained details up and high-level semantic information down through the network, making sure that objects of different sizes are detected accurately.

Head

The head handles the last prediction tasks, such as bounding box regression, confidence scoring of class, and auxiliary outputs like segmentation masks or pose key points. One of the main advancements in YOLOv8 is transitioning to an entirely anchor-free head. In contrast to anchor-based approaches depending on prior boxes, YOLOv8 predicts object center points and sizes directly employing Dynamic K Matching and Distribution Focal Loss (DFL). This leads to more flexible and accelerated training, better localization performance, and generalization to new data distributions.

4.4.2Training Process and Hyperparameters

The model was trained on a stoked dataset using the following hyperparameters

Batch Size 32 literacy Rate 0.001 with a cosine annealing scheduler.

Optimizer Adam for effective grade descent.

Ages 100 to insure confluence.

4.4.3Tools and fabrics

YOLOv8 was enforced using the PyTorch frame. Libraries like OpenCV were used for preprocessing and addition, while GPU acceleration(NVIDIA CUBA) enhanced training speed.

Evaluation Metrics

The model's performance was assessed using the following criteria

True Positive(TP): The diseased area will be correctly detected by the model.

False Positive(FP): The model wrongly detects the disease.

False Negative(FN): The model doesn't identify the disease which is actually present.

IoU (Intersection over Union): This measures how much the predicting bounding box overlaps with the ground truth.

Mean Average Precision(chart) Evaluates discovery delicacy by comprising perfection values across different crossroad-over-union(IOU) thresholds.

Precision: Measures the proportion of rightly linked complaint cases among all findings.

Precision= TP / TP+FP

Recall: It reflects the proportion of factual diseased areas rightly linked.

Recall= TP / TP+FN

mAP@0.5: It measures how accurate the model is detecting objects across all the images and the classes. It considers both precision and recall at different confidence thresholds.

4.5 Flowchart

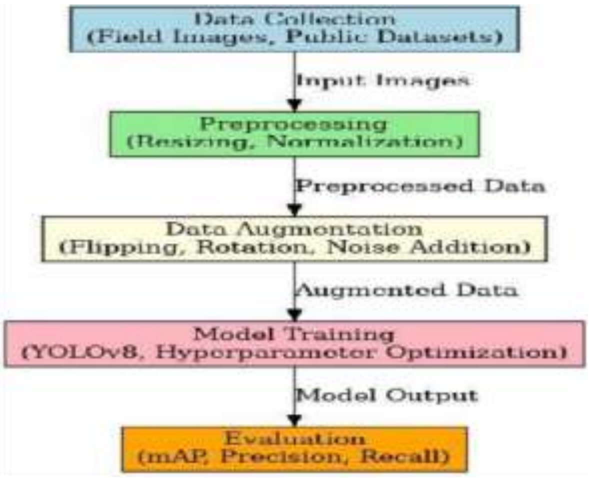

Figure1: Flowchart for sugarcane and mango leaf disease detection using yolov8.

The above Figure1 flowchart includes the following steps:

1.Data Collection:Field images and public datasets.

2.Preprocessing: Resizing and normalization.

3.Data Augmentation: Techniques like flipping, rotation, and noise addition.

4.ModelTraining:YOLOv8 with hyperparameter optimization.

5.Evaluation: Performance assessment using mAP, Precision, and Recall.

5. RESULTS AND DISCUSSION

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The YOLOv8 model has demonstrated outstanding performance in the detection of sugarcane and mango leaf diseases, exhibiting a high level of accuracy, precision, and recall. These results affirm the potential of YOLOv8 in agricultural applications where real-time disease detection is essential for timely intervention and management. This section provides a detailed analysis of the quantitative results, compares YOLOv8 with other detection models, presents visual outcomes, and evaluates the impact of data augmentation on model performance.

5.1. Quantitative Results

The YOLOv8 model was trained and evaluated on a dataset consisting of sugarcane and mango leaf images, which included both healthy and diseased leaves. The model achieved a Mean Average Precision (mAP@0.5) of 91.7%, showcasing its exceptional ability to detect and localize leaf diseases. The training accuracy of 94.3% further highlights the robustness of the model, indicating that it has learned to effectively distinguish between healthy and diseased leaves.Precision and recall values of 90.5% and 88.6%,respectively, demonstrate that YOLOv8 consistently detects diseased regions with minimal false positives and false negatives.

The model's performance in detecting sugarcane and mango leaf diseases confirms YOLOv8's capacity to handle complex agricultural imagery, which may include varying leaf structures, backgrounds, and lighting conditions. These high metrics ensure that the model can be reliably deployed in real-world scenarios for automatic disease detection in agricultural fields, thus reducing the need for manual inspection and enabling faster decision-making.

5.2. Comparison with Other Detection Models

To further validate the performance of YOLOv8, a comparison was conducted with two widely used object detection models: YOLOv4 and YOLOv5. The comparison is based on several critical metrics: mAP@0.5, precision, recall, and inference time. The results, summarized in the table below, provide a clear indication of YOLOv8's superiority over its predecessors.

Model	map@0.5	Precision	Recall	Inference time
YOLOv4	85.2%	83.5%	80.4%	38
YOLOv5	89.4%	87.0%	85.2%	28
YOLOv8	91.7%	90.5%	88.6%	22

Table1: Comparison with YOLOV4, YOLOV5 and YOLOV8

As seen in the Table1, YOLOv8 outperforms both YOLOv4 and YOLOv5 in all major metrics. With an mAP@0.5 of 91.7%, YOLOv8 surpasses YOLOv5 (89.%) and YOLOv4 (85.2%) in terms of accuracy. Furthermore, YOLOv8 exhibits higher precision (90.5%) and recall (88.6%) compared to the other two models, indicating its improved ability to detect and localize diseased regions without misidentifying healthy areas. Additionally, YOLOv8 demonstrates the fastest inference time at 22 milliseconds, which is crucial for real-time applications such as autonomous disease detection in agricultural environments.

The combination of superior performance metrics and fast inference time makes YOLOv8 an ideal choice for deployment in time-sensitive agricultural settings where rapid disease detection is necessary to prevent crop damage and reduce losses.

5.3. Visual Results

The visual output of YOLOv8 further reinforces its effectiveness in detecting leaf diseases. In the following figure, two scenarios are illustrated: one with healthy leaves and another with diseased areas.

Healthy Leaves: In images containing healthy leaves, no bounding boxes are drawn, confirming that the model has correctly identified the absence of diseases.

Diseased Areas: For images with diseased leaves, bounding boxes are drawn around the affected regions, with confidence scores displayed to indicate the model’s certainty in its predictions .

These visual results highlight YOLOv8's capability to handle complex and cluttered backgrounds, a common challenge in agricultural image analysis. The model can accurately distinguish between healthy and diseased areas even in the presence of other plant features or environmental factors, such as varying lighting conditions and shadows.

5.4 Impact of Data Augmentation on Performance

Data augmentation played a pivotal role in enhancing the performance and generalization ability of YOLOv8. The model was trained both with and without data augmentation to assess its impact on the overall results. The following Table 2 summarizes the performance metrics for both cases:

Metric	Without Augmentation	With Augmentation
mAP@0.5	84.6%	91.7%
Precision	85.3%	90.5%
Recall	82.1%	88.6%

Table2: Comparison with data augmentation

Without data augmentation, the model achieved a respectable mAP@0.5 of 84.6%, precision of 85.3%, and recall of 82.1%. However, when data augmentation techniques such as flipping, rotation, and noise addition were applied, a significant improvement was observed. The mAP@0.5 increased to 91.7%, precision rose to 90.5%, and recall improved to 88.6%. These results clearly indicate that data augmentation enhanced the model's ability to generalize across different disease symptoms, leaf orientations, and image conditions, making it more robust and less prone to overfitting.

The use of data augmentation allows the model to learn from a more diverse set of images, which is particularly valuable in agricultural settings where variations in leaf diseases, environmental factors, and plant varieties are common. This approach ensures that the model can adapt to new, unseen data, improving its performance when deployed in real-world agricultural environments.

Let me generate the following for better clarity:

1.Bar Graph: Showing performance metrics for YOLOv4, YOLOv5, and YOLOv8.

2.LineGraph: Showing the impact of data augmentation on mAP, Precision, and Recall.

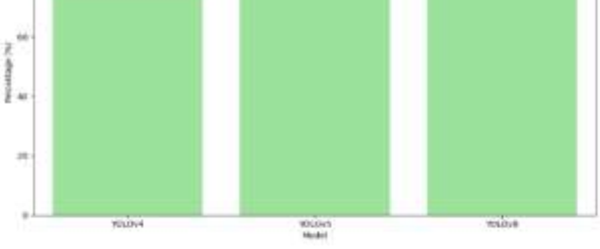

Figure2: Performance metrics comparison for Yolo models for leaf disease detection.

Here are the generated graphs:

Performance Metrics Comparison: In Figure2 bar graph compares the performance metrics (mAP, Precision, Recall) of YOLOv4, YOLOv5, and YOLOv8.

Figure3: Impact of data augmentation on Yolo model performance metrics.

Impact of Data Augmentation on Performance: This line graph in Fig3 shows how data augmentation impacts mAP, Precision, and Recall.

6.APPLICATIONS AND BENEFITS

Applications and Benefits of YOLOv8 in Agriculture:

The YOLOv8 model holds significant potential for revolutionizing agricultural monitoring systems. By accurately detecting and localizing diseases in sugarcane and mango leaves, YOLOv8 can be integrated into advanced monitoring platforms to automate disease detection and improve the overall efficiency of agricultural practices. With its ability to process images in real time and deliver high-precision results, the model can be deployed in a variety of agricultural applications, enhancing productivity and reducing manual labor.

One of the key applications of YOLOv8 in agriculture is its potential integration with drones or IoT devices. Drones equipped with high-resolution cameras can capture images of large crop fields, and YOLOv8 can process these images in real-time to identify diseased plants.

This integration allows for the rapid identification of problem areas, enabling farmers to take timely action. Drones can cover vast areas efficiently, capturing data from hard-to-reach locations, such as large plantations, which would otherwise require significant time and manpower. Additionally, IoT devices placed throughout the fields can collect environmental data, such as soil moisture and temperature, which can be used in conjunction with the disease detection model to provide a comprehensive monitoring system. This synergy between IoT devices, drones, and YOLOv8 can enable farmers to adopt a more data-driven approach to crop management.

The benefits of YOLOv8's application in agricultural monitoring extend directly to farmers. By automating the disease detection process, farmers can significantly reduce the time and effort spent on manual inspections. Early detection of leaf diseases enables farmers to take preventive measures, such as targeted pesticide application, which minimizes the spread of diseases and reduces the need for widespread chemical treatments. This approach not only improves the health of crops but also reduces costs associated with pesticide use.

Furthermore, the precision and speed of YOLOv8 contribute to minimizing crop losses. With the ability to quickly identify diseased areas, farmers can implement timely interventions, preventing the further spread of diseases that might otherwise lead to significant crop damage. This early intervention can enhance crop yield and quality, directly benefiting farmers by ensuring better harvests and, ultimately, higher profits. The adoption of such technologies also supports sustainable farming practices by reducing the reliance on chemical inputs and promoting more environmentally friendly methods of disease control.

7.CHALLENGES AND FUTURE WORK

7.1Challenges:

Despite the impressive performance of YOLOv8 in detecting leaf diseases, there are several challenges and limitations that need to be addressed for broader application in agriculture. One limitation is the dependency on high-quality, labeled datasets for training the model. The performance of YOLOv8 heavily relies on the diversity and quantity of training data. In many agricultural settings, obtaining large, well-labeled datasets can be time-consuming and costly, particularly when dealing with rare or less common diseases. Additionally, the model may struggle with detecting diseases in images with varying lighting conditions, backgrounds, or occlusions, such as when the leaves are partially hidden or covered by environmental factors like dust or water droplets.

Another challenge is the model's ability to generalize across different crop varieties and regions. YOLOv8 Has shown excellent performance on the specific dataset it was trained on, but its adaptability to other crops or geographic areas with different disease patterns may require further fine-tuning or retraining.

7.2Future Enhancements:

To overcome these challenges and enhance the model's capabilities, several improvements can be considered:

1. Larger and more diverse datasets : Expanding the dataset to include a broader range of crops, diseases, and environmental conditions will help improve the model's generalization and robustness. Including additional disease types and variations in symptoms will allow the model to identify a wider array of conditions and better support global agricultural needs.
2. Multi-crop Disease detection : Future work can focus on developing models capable of detecting diseases across different crops simultaneously. This would make the technology more versatile and useful for farmers working with multiple crops.
3. Improved handling of complex environmental factors : Enhancing the model's ability to handle varying environmental conditions, such as lighting changes, shadows, and occlusions, will improve its performance in real-world field conditions. By addressing these challenges and incorporating these enhancements, YOLOv8 can become an even more powerful tool for automated, real-time disease detection in agriculture.
4. By addressing these challenges and incorporating these enhancements, YOLOv8 can become an even more powerful tool for automated, real-time disease detection in agriculture.

8.CONCLUSION

In this study, the YOLOv8 model demonstrated exceptional performance in detecting sugarcane and mango leaf diseases, with high metrics such as a Mean Average Precision (mAP@0.5) of 91.7%, precision of 90.5%, and recall of 88.6%. These results highlight YOLOv8's effectiveness in accurately identifying and localizing diseased regions in plant leaves, offering significant promise for agricultural disease management. The integration of data augmentation techniques further enhanced the model's generalization capability, improving its performance in diverse real-world conditions.

The comparison with earlier YOLO versions, YOLOv4, and YOLOv5, underscored YOLOv8's superiority in terms of both accuracy and inference time. The faster inference time of 22 milliseconds makes YOLOv8 highly suitable for real- time applications, where timely disease detection is critical for minimizing crop losses. Additionally, the model's potential integration with drones and IoT devices can provide farmers with a comprehensive and automated monitoring system, streamlining the process of disease detection and intervention.

These findings have substantial significance for the agricultural industry. By automating the detection of leaf diseases, YOLOv8 can help farmers reduce manual labor, lower pesticide costs, and minimize crop losses through early intervention. This model contributes to the advancement of precision agriculture, where technology enables more sustainable and efficient farming practices, ultimately leading to improved crop yields and higher profits.

Finally, the research highlights the transformative potential of AI-powered solutions like YOLOv8 in agriculture. The integration of such advanced technologies can not only enhance crop management but also play a pivotal role in addressing the challenges posed by climate change and global food security. Future work should focus on expanding the model's capabilities to detect a wider range of diseases across various crops, further solidifying YOLOv8's contributions to agricultural technology.

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