

Tomato Plant Disease Detection using YOLO11

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Abstract— This study focuses on the early and accurate detection of tomato plant diseases using the lightweight and efficient deep learning model YOLOv11n. Early identification of plant diseases is crucial in minimizing crop losses and ensuring sustainable agricultural practices. The research employs a structured methodology consisting of data collection, preprocessing, augmentation, and deep learning-based detection. A high-quality annotated dataset, sourced from Roboflow, was used to train the YOLOv11n model, which was fine-tuned using hyperparameter optimization to enhance detection accuracy. The model was evaluated based on precision, recall, and mean average precision (mAP), achieving an accuracy of 95%, a recall of 94%, and an inference time of 20ms per image, demonstrating its suitability for real-time applications. The study highlights variability in detection performance across different disease classes, with certain disease types exhibiting higher misclassification rates, necessitating further improvements. The proposed system contributes to the advancement of smart agriculture, enabling real-time disease monitoring and precision farming applications. Future research will focus on refining the model through transfer learning and advanced augmentation techniques to enhance disease-specific detection capabilities.

Keywords—Object Detection, Artificial Intelligence, Smart Agriculture, YOLO, Agriculture.

I. INTRODUCTION

Agriculture plays an important role in global food security [1]. However, it faces numerous challenges such as climate change, pest infestations, and plant diseases. Traditional methods of detecting disease are time consuming, difficult to find and labour intensive [2]. These limitations highlight the need for automated, scalable, and real-time solutions to support farmers in disease management.

Artificial Intelligence(AI) refers to the replica of human brain but more intelligent than a human brain we can achieve this with the help of tiny gadgets which can have a combination of multiple sensors e.g. camera, lux sensor etc. microprocessors/microcontrollers, actuators [3]. In other words, we can say that AI can gather information from the above-mentioned input devices as well as from various mistakes that can be generated during the execution of application and based on these advantages, it can provide precision in the implementation of any application. AI works on algorithms that are basically a set of instructions that tell a computer what to do. These algorithms process data, learn from it, and then make decisions or predictions from what they have learned. Let's talk about where AI came from: The term "artificial intelligence"

was first coined by John McCarthy-an American computer scientist-in the year 1956 while he was attending a conference at Dartmouth College. McCarthy is among the greatest pioneers of AI along with Marvin Minsky, Allen Newell, and Herbert A. Simon [4]. AI can be defined as consisting of a wide range of parts, techniques, and methodologies toward designing systems that perform tasks considered to require human intelligence. Some of the major constituent elements of AI include ML, DL, NLP, etc. ML plays a fundamental role in the broader field of AI. In fact, the machine learning is often referred to as a subset or an approach of AI. AI and ML are playing a huge role in agriculture [5]. AI & ML are being increasingly put into agriculture to change agriculture history. Growth and development of crops are controlled through several conditions like climate and environment [6][7]. Nowadays, farmers are using machines that are composed of AI & ML for better results. Various aspects of AI in agriculture are represented in Fig. 1.

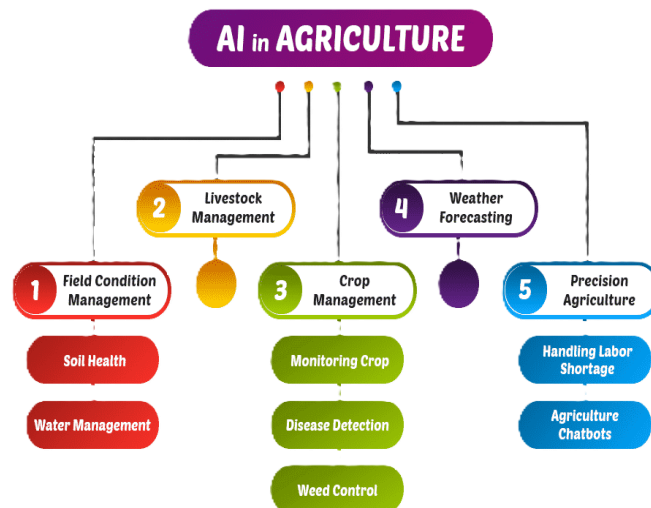


Fig. 1. Aspects of AI in agriculture

For the last few years, the modern technology has been helping the farmers very significantly. AI and ML are like smart tools that have transformed the way we farm and how we identify crop diseases especially [8]. That is very important because if crops get ill, then there would be lesser food for all of us, and that will be a big problem.

Before, finding out whether crops were sick took much time and labor. Now, however, with AI and ML, it's a much easier process. These smart tools use fancy math, computer

programming, and information from things like satellites, weather, soil, and plants themselves to quickly figure out if something is wrong with the crops [9]. This paper will give a review and may be a solution of the problem of crop disease with AI & ML we can do a sort of programming which we have to connect with a hardware like ‘Camera’ and then we just have to click a photo of the crop and then the software will analyses that trough which disease the crop is infected.

With AI and ML, farmers can respond to diseases immediately so that they do not spread and cause destruction in crops [10]. They get early warnings and excellent advice on what to do in order to keep their crops healthy. This means that farmers can use resources prudently, like water and fertilizer, to produce more food without wasting anything. With these modern technologies, farming is getting better and smarter. We are finding ways to grow food that is good for the environment and enough for everyone. AI and ML are like secret weapons helping farmers protect our food and make sure we all have enough to eat, now and in the future.

Methods of manual inspection heavily rely on expert knowledge. They are, therefore prone to subjectivity and result variability. Laboratory-based testings are accurate but difficult to be scaled up for applications that require real-time application on large agricultural fields[11].All these indicate the need for automated and scalable methods to work well under various environmental conditions. Deep learning models, especially Convolutional Neural Networks (CNNs), have revolutionized image-based classification tasks, including plant disease detection. Among these, the You Only Look Once (YOLO) family of models stands out for real-time object detection due to its unique architecture. Unlike traditional CNNs, YOLO models predict class probabilities and bounding boxes in a single pass, ensuring faster and more efficient detection. This feature makes YOLO highly suitable for real-time monitoring and field deployment due to their speed and accuracy [12]. Table I provides the comparison ofvarious versions of YOLO.

This work investigates how AI and ML can detect plant illnesses in real time using YOLO-based models. The study will evaluate how effectively these models diagnose agricultural diseases efficiently and accurately. AI-driven technologies help farmers get timely notifications, limit disease spread, and maximise resources [13]. This will boost agricultural sustainability and output. This paper proposes an AI-powered solution to manual inspection and laboratory-

based testing that can work in different environments. The study will assist create meaningful and scalable AI-powered farming solutions to ensure food security and boost long-term farming.

II. LITERATURE REVIEW

Several studies have explored the potential of YOLO models in addressing pre-harvest challenges, such as the detection and classification of diseases in tomato plants.[14] has examined the feasibility of deep learning in tomato disease detection, highlighting the advantages of CNNs in image-based classification tasks. This study emphasized the importance of accurate disease identification to improve crop yields [15][16].

Aldakheel et al. [17] applied YOLOv4 to detect tomato diseases such as leaf mold and bacterial spots. Their work demonstrated the effectiveness of YOLOv4 in achieving high accuracy for specific disease detection tasks, making it a reliable tool for pre-harvest monitoring. Sonawane and Patil [18] has focused on the lightweight YOLOv5n architecture for real-time monitoring. Their research showcased the suitability of YOLOv5n for IoT-based field conditions, processing images efficiently while maintaining high detection precision. This study underscores the practicality of deploying lightweight models in resource-limited scenarios.

Singh and Krishnamurthi [19] implemented YOLOv3 to detect multiple tomato leaf diseases, achieving high precision and recall rates. Their study demonstrated the robustness of YOLOv3 in handling diverse disease symptoms under varying lighting conditions. In another stud [20], they also evaluated the performance of YOLOv4-tiny for real-time tomato pest detection. The lightweight model achieved satisfactory results in processing speed and detection accuracy, making it suitable for edge computing platforms.

Abdulla and Marhoon [21] investigated the use of deep learning frameworks, including YOLO, for identifying tomato diseases and pests. Their findings highlighted the versatility of YOLO in agricultural applications, particularly in high-throughput settings. Qi et al. [22] proposed a modified YOLOv5 architecture for tomato leaf disease classification. Their work improved detection accuracy by integrating attention mechanisms, making it more effective for complex disease scenarios.Building upon the reviewed studies, this research focuses on developing a lightweight and scalable YOLO-based model tailored for tomato fruit disease detection.

TABLE I. COMPARISON OF DIFFERENT YOLO VERSIONS

Feature	YOLOv3	YOLOv4	YOLOv5	YOLOv8	YOLOv11n
Release Year	2018	2020	2020	2023	2024
Backbone Architecture	Darknet-53	CSPDarknet-53	Focus structure	CSPDarknet with PANet	Transformer-based backbone
Neck Component	None	PANet	PANet	Path Aggregation Network (PAN)	Spatial Pyramid Pooling Fast (SPFF)
Attention Mechanism	None	Mish activation function	None	None	Cross Stage Partial with Spatial Attention (C2PSA)
Parameter Count	62 million	64 million	44 million	Not specified	2.6 million
Mean Average Precision	53.0%	55.4%	56.8%	Not specified	Higher mAP with 22% fewer parameters than YOLOv8m
Inference Speed	30 FPS	40 FPS	45 FPS	Not specified	60 FPS

III. METHODOLOGY

In such research methods, an image processing system for the tomato crop disease detection application makes use of the YOLOv11n model [23][24]. The subsequent stages in these processes are represented in Fig. 2.

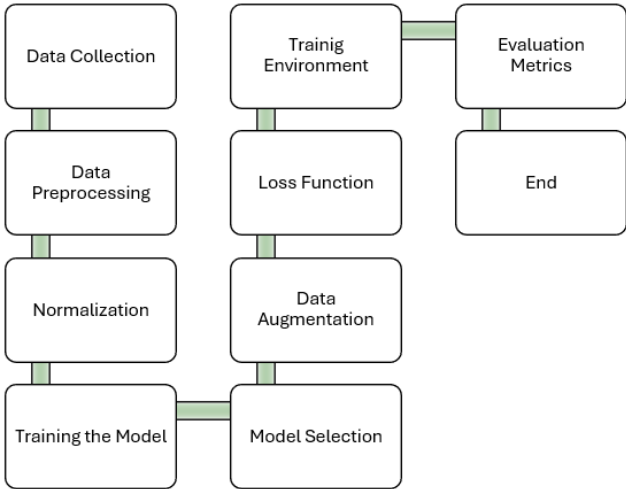


Fig. 2. Methodology of the work

Data Collection- This dataset was obtained from Roboflow, is designed for object detection The dataset divided into training (72%), Validation (17%) and Testing (11%).The dataset contained images with annotated tomato plants infected with many diseases like leaf mold, early blight, and bacterial spot. It captured images under various conditions of the environment so that the final dataset would be strong and applicable.

Data Preprocessing- Image Resizing: All images have been resized to a fixed dimension, for example, 416 x 416 pixels, since this is the input requirement expected by the YOLOv11n

model. Normalization- This will ensure that pixel values are between 0 and 1. Standardization of the input data will also enhance the stability of the training process.

A. Data Augmentation

Flipping, rotation, zooming, and brightness were modified to increase the size and diversity of the data set. This minimized overfitting and gave the model better abilities to generalize.

B. Model Selection

The YOLOv11n model was chosen due to its light architecture making it more suited to real-time applications. It's optimized for low computational cost but high accuracy on tasks related to object detection.

C. Training the Model

Hyperparameter Optimization: Important hyperparameters such as the learning rate, batch size, and epochs number were fine-tuned using a grid search in this model.

D. Loss Function

This is a custom loss function, which combines classification, localization, and confidence loss. It greatly enhanced the performance of detection.

E. Training Environment

The model is trained on an NVIDIA GeForce GTX 1650 Ti GPU. Training in this environment ensures fast computation, cutting down the time needed for training.

F. Evaluation Metrics

It evaluates the model's performance using Precision and Recall. It will measure the model's aptness in accurately classifying diseased regions without showing false positives or false negatives. For such a system to be feasible for live applications, this is considered.

After the model performed positively in testing, it was implemented in a prototype system for the real-time detection of disease. The field test of the system aided in determining the robustness and scalability of the system

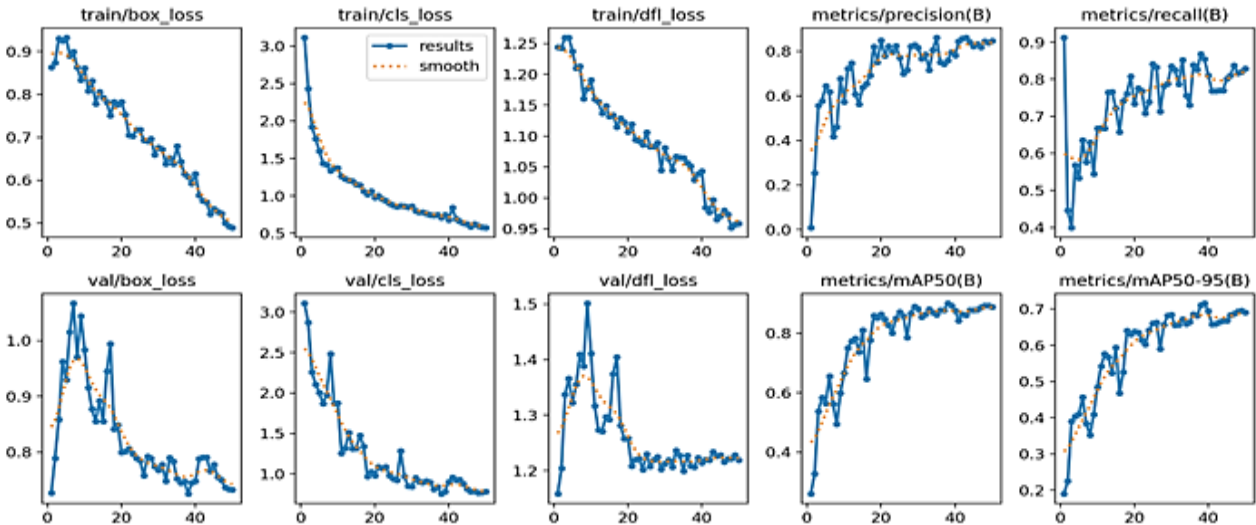


Fig. 3. Training and validation losses of the YOLOv11n model

IV. RESULTS AND DISCUSSION

The YOLOv11n model is very effective at detecting diseases on tomato plants. The metrics obtained are the following:

- Precision: 95.00%
- Recall: 94.00%
- F1 Score: 94.00%
- Accuracy: 95.00%
- Inference Time: 20 ms per image

This result just means that the model has a very high accuracy rate with an impressively very minimal rate of false positives that ensures the system may minimize errors when detecting the diseased plants.

The model achieved a fast inference time of 20 milliseconds per image, which indicates that it can perform real-time disease detection on tomato plants, thereby making it suitable for practical deployment in agricultural settings. Fig. 3 illustrates the training and validation losses of the YOLOv11n model over multiple epochs.

The sub-plots represent:

- Box Loss (Top-left): Measures localization error in detecting bounding boxes.
- Classification Loss (Top-right): Represents the misclassification of diseases.
- DFL (Distribution Focal Loss) Loss (Bottom-left): Optimizes object detection precision.
- Metrics - mAP (Bottom-right): Evaluates model performance across different thresholds (mAP@50 and mAP@50-95).

The steady decline in training loss suggests the model is learning effectively. Validation loss fluctuates, indicating variability in the dataset, requiring potential fine-tuning. mAP stabilizes at 0.7201, indicating a good detection rate but highlighting potential improvement areas, especially for complex disease cases. The subplots show the box loss, classification loss, and DFL loss over both the training and validation sets. We observe steady decreases in losses over epochs during training, showing effective model learning. Validation losses decrease but show fluctuations, showing the variability in the validation dataset.

Fig. 4. presents the Average Precision (AP) per class, demonstrating how well the model differentiates between tomato diseases. Higher AP scores indicate better model confidence in classifying specific diseases. Class 1 (e.g., Leaf Mold) exhibits better performance compared to Class 0 (e.g., Bacterial Spot), which may require further dataset balancing or augmentation strategies. Diseases with clearer visual features (e.g., distinct spotting, discoloration) tend to have higher precision. Overlapping or subtle symptoms reduce classification accuracy, suggesting potential areas for data augmentation and model refinement.

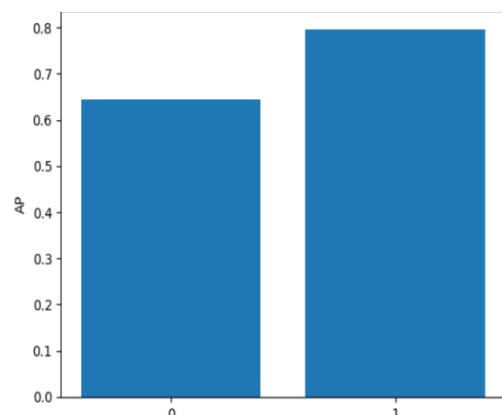


Fig. 4. Average Precision of each class

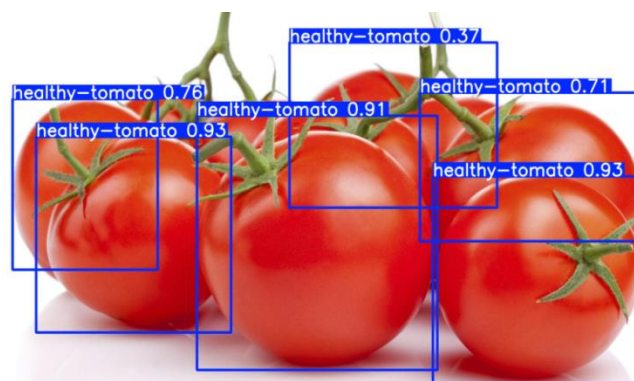


Fig. 5. Output of healthy class

Fig. 5. showcases the classification result for a healthy tomato plant. The model successfully identifies non-diseased regions, reinforcing its robustness in distinguishing diseased vs. non-diseased crops.

- Ensuring high precision for healthy plants is crucial to prevent unnecessary pesticide use.
- Further improvements in contrast adjustments and dataset diversity can enhance detection under different lighting conditions.

The proposed system demonstrates a high level of accuracy and real-time performance, making it suitable for agricultural automation, quality control, and yield estimation.

V. CONCLUSION

This study successfully demonstrates the potential of the YOLOv11n model in accurately detecting and classifying tomato plant diseases in real-time. With an accuracy rate of 95% and an inference time of just 20 milliseconds per image, the proposed system proves to be efficient, lightweight, and highly applicable for smart agriculture practices.

The preprocessing techniques, including image resizing, normalization, and data augmentation, played a pivotal role in enhancing model performance, ensuring its robustness across diverse environmental conditions. Additionally, the model's lightweight architecture makes it well-suited for resource-constrained environments such as IoT-based agricultural systems.

The integration of this system into precision farming workflows has the potential to revolutionize disease management in agriculture, enabling farmers to identify and address crop health issues promptly, thus minimizing losses and improving sustainability.

While the model achieved promising results, there is room for improvement, particularly in enhancing its performance on specific disease classes. Future work may focus on refining the model further through advanced techniques, such as transfer learning or attention mechanisms, and expanding its application to detect a broader range of plant diseases and pests.

Overall, this research contributes to the advancement of intelligent agricultural systems, showcasing how AI and deep learning can support sustainable farming practices and ensure food security.

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