Research Paper

Cotton care: YOLO-powered cotton leaf disease detection

Aruna Pavate[1*], Ashwini A. Patil[2], Shradha Birje[3], Archita Agar[4], Saman M. Almufti[5]

[1*,3,4]Information Technology, Thakur College of Engineering and Technology, University of Mumbai, Mumbai, India.
[2]Department of AIML, M.S. Bidve Engineering College, Latur, Maharashtra, India.
[5]Department of Information Technology, Technical College of Duhok, Duhok Polytechnic University Iraq.
Department of Information Technology, Technical College of Informatics Akre, Akre University for Applied Sciences Iraq.

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ABSTRACT

Early detection of plant diseases is an important factor for maintaining crop health and enhancing agricultural productivity. Early observation of symptoms of diseases, followed by accurate treatment in cotton growing, can greatly reduce loss of yield and save unnecessary pesticides. Recent developments in deep learning and computer vision have pushed the automated disease detection based on leaf images to be scalable and applicable in real-world agricultural practices. In this paper, we introduce a cotton disease detection technique with four YOLO (You Only Look Once) based object detection models: YOLOv5, YOLOv6, YOLOv8, and the latest YOLOv11. These models are trained on a generated dataset of annotated cotton leaf images capturing multiple symptoms like leaf enation, sooty mold, various curly forms, as well as healthy leaves. The purpose is to accurately classify and localize the disease-affected patches so as to enable real-time decisions in precision farming. The result showed that among the tested models, YOLOv11 presented the best performance with 98.2% precision, 99.3% recall, 99.6% mAP@0.5, and 0.78 mAP@0.5:0.95. YOLOv8, YOLOv6, and YOLOv5 performed well too. The input devices emphasize the significance of preprocessing for real-world applications to achieve robustness of the model to different lighting conditions. The results indicate that the proposed method can be used as a good and effective tool for automated cotton disease prediction and integrated pest management.

Corresponding Author:
Aruna Pavate
Information Technology, Thakur College of Engineering and Technology, University of Mumbai, Mumbai, India.
Email: arunaapavate@gmail.com

1. INTRODUCTION

The application of machine learning (ML) methods in many fields, such as agriculture, has changed the way we solve problems. To be specific, plant disease prediction and detection were also highly influenced by developments in both computer vision and deep learning. Recently, research has shifted to using ML algorithms for the identification of plant diseases, increasing the production in agriculture and food security [1], [2]. Disease forecasting in plants, specifically in cotton, has vital significance for maximizing production, quality, and minimizing the environmental effects of pesticides [1]. Machine learning-based techniques, particularly deep learning architectures, have been demonstrated as successful approaches in automating disease detection by using images of plant leaves [3], [4].

There are many challenges to the agriculture industry, especially with cotton farming, which is very vulnerable to diseases. Cotton, as an essential cash crop worldwide, especially in India, undergoes substantial yield loss due to diseases like bacterial blight, powdery mildew, and leaf spot [5]. In India, which accounts for around 22% of global cotton production, the importance of disease management strategies to sustain the agricultural economy cannot be overemphasized [6]. Cotton production in tons is shown in Figure 1. Although there have been developments in farming methodologies, the process of detecting cotton plant diseases remains manual and time-consuming, and is inevitably error-prone and inconsistent due to environmental variability [7]. Therefore, there is a strong demand for an automated system that can diagnose plant diseases/interact with the user in real time and under a variety of environmental conditions [8].

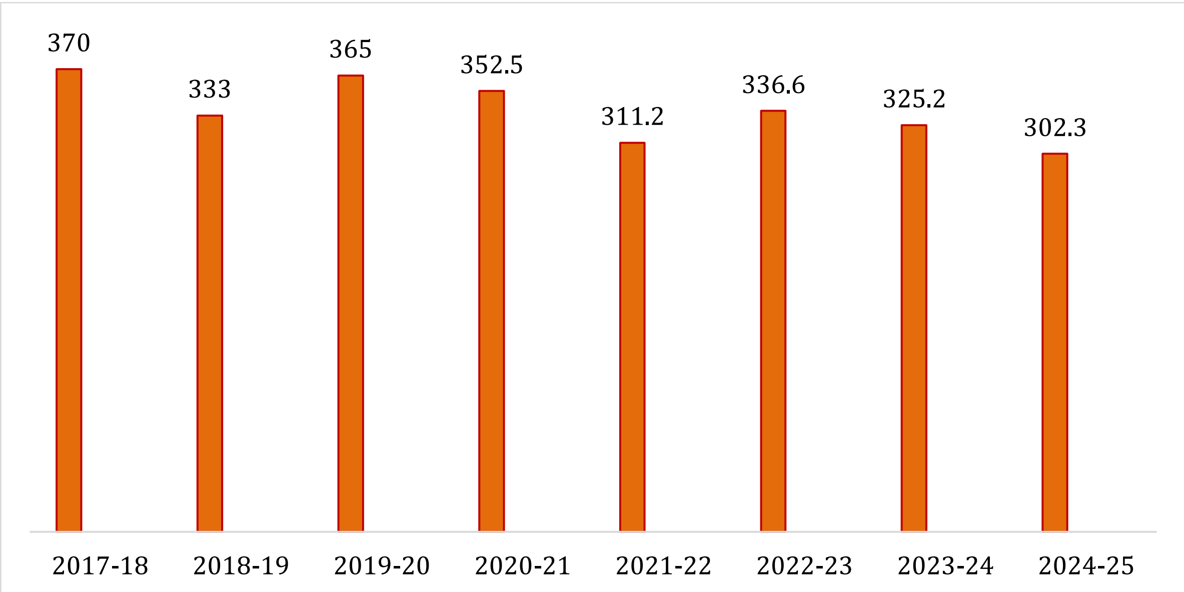

Figure 1. Production of Cotton in India (Lakh bales of 170 kg)

Machine learning algorithms, including Convolutional Neural Networks (CNNs) and state-of-the-art object detection models such as YOLO (You Only Look Once), have proven their effectiveness for image-based plant disease detection [8], [9], [10]. CNNs are well known for processing and classifying complex image data, which makes them more suitable for detecting disease from leaf images. On the other hand, object detection algorithms such as YOLO are very fast in detecting the disease and can also determine the location of the disease in the image, which is essential to take accurate treatment [11].

This paper is focused on designing a generalized framework of cotton disease detection using the latest deep learning models, i.e., YOLOv5, YOLOv6, YOLOv8, and YOLOv11. We assess these models in terms of their capacity to detect and distinguish several diseases in a cotton plant, so that the farmer can make the right decision in real-time. The EfficientNet is used as a feature extractor and integrated with YOLO to detect objects such as worms or other disease symptoms on leaves. The proposed method aims to enhance the accuracy of predicting a disease, allowing for faster response time and helping to minimize crop damage [12].

YOLOv5 and YOLOv6 also achieved promising results with mAP@0.5 of 96.4% and 97.1%, respectively [13]. YOLO versions were evaluated for the detection of plant diseases. This study extends upon previous work where various versions of YOLO have given remarkable results. Although YOLOv8, with 97.4% precision, is very powerful, it still lagged behind YOLOv11, which delivered the best results with a precision of 98.2% and a recall of 99.3% [14]. These systems have a significant edge over conventional techniques for faster and more accurate detection of diseases and are capable of being used in real-time or in the field. With the introduction of deep learning, the precision and time consumption of the plant disease detecting systems were greatly enhanced. Convolutional Neural Network (CNN) based approaches proved to be very successful in extracting features associated with disease from leaf images and to facilitate the automation of the disease recognition process [15], [16], [17].

Traditional CNN models, however, primarily address image classification and thus these models are not well-suited for object localization in real-time field use. Considering these limitations, various versions of detector networks based on the YOLO (You Only Look Once) architecture have been proposed and gained significant attention. Comparison studies of different types of YOLO outputs have so far demonstrated that it exhibits great detection speed and location precision with lower computational cost in comparison to a traditional CNN-based method [13]. In addition, an advanced system for disease detection based on YOLOv8 with superior robustness in a complicated farm environment has been introduced [18]. Lightweight YOLO-based models have been proven successful in real- time detection of cotton diseases on a naturally constrained device in natural field conditions, revealing that they are capable of practical application in the decision support systems for agriculture [19]. It implies a preference for new corresponding frameworks based on YOLO for plant disease recognition in the row of expert, scalable, and truthful solutions. This paper proposes to improve the cotton disease treatment system performance by incorporating an EfficientNet-based feature extractor for disease localization and classification with YOLO, in the spirit of a holistic solution.

The following section discusses the related work methodology and experimental design used to evaluate the effectiveness of the proposed model and introduces the data sets for training and testing.

2. RELATED WORK

Detection of plant diseases is the key research to enhance the agricultural yield, quality of crop, and food security. According to the recent surveys, there is a trend towards employing machine learning (ML) and deep learning (DL) based solutions for the automation of disease diagnosis, which offers significant superiority to traditional manual inspection methods in accuracy, scalability, and operation overheads [1], [3], [4], [5]. Deep learning methods have attracted great attention due to the fact that it can learn discriminative features directly from plant images without the need for handcrafted feature extraction [2], [17].

Earlier works were concentrated on Convolutional Neural Networks (CNNs) to classify diseases. Reviews diagnosed by Li [3], [4], [14] confirm the best result in deep learning-based plant disease detection and classification, rather than using conventional machine learning models. Sladojevic [15] showed the performance of deep neural networks in identifying plant diseases with leaf images, and [16] observed high classification accuracies for different crop species with deep learning models. Regarding the need for real-time and field-applicable agricultural monitoring, object detection frameworks have shown potential as a substitute for the traditional image classification models.

The YOLO (You Only Look Once) type of architecture performs object location and classification in one step, allowing for fast and precise disease detection. [20] Presented YOLOv5, which provides the best trade-off between accuracy and speed. Next, [21] introduced YOLOv7, the current state-of-the-art, which facilitates the integration of a series of effective training methods and architectural modifications for boosting object detection efficacy. The progressive versions of YOLO have been shown to exceed conventional methods in accuracy on localization, speed of inference, and real-time capacity [13] in this application of agronomy.

Recent studies have also upgraded YOLO-based detection models to be more fit for real-world agriculture. [18] Proposed an improved YOLOv8-based vegetable disease recognition, and the accuracy and robustness are improved under the conditions of a greenhouse environment. Likewise, [19] introduced a lightweight cotton disease detection model for natural field environments on resource-limited devices. To remedy the challenge of small lesion detection and complex background, [7] suggested a cotton leaf disease recognition model based on overall feature extraction and better recognition of small targets.

Sustainable cotton growing depends on multi-use cotton, and the diseases affecting multi-use cotton are the same as those affecting fibre quality and yield. A systematic review by [6] highlighted the necessity of adopting emergent technologies to support sustainable cotton production. In this regard, [8] presented a YOLO-based cotton plant health monitoring system that predicts a higher number of disease states with more precision. In addition, [9] presented the intelligent crop recommendation based on ensemble supervised clustering methods, and [10] have brought out the potential of agentic AI in defining smart and sustainable precision agriculture systems.

Apart from disease detection, ML algorithms were also applied to crop yield prediction and decision support systems in agriculture with promising results. [11] Confirmed that the RF models (Random Forest Models) are effective models for the global and regional crop yield prediction. In the same way, [12] used a Random Forest procedure to project crop yield for the major cities of Maharashtra, signifying the utility of knowledge-based techniques in farm planning and monitoring.

The literature shows a definite trend of shifting traditional machine learning methods to deep learning-based disease detection systems, critical analysis of the same is mentioned in Table 1. Traditional machine learning approaches rely on hand-crafted features and usually are not robust to changes in the environment [1], [5]. While CNN-based models greatly increased disease classification accuracy, the majority of them concentrate on image-level classification and do not have exact localization power for commercial agricultural monitoring [15], [16]. Significantly, YOLO based object detection methods have been capable of overcoming most of these constraints with disease localization and classification at relatively high scanning speed. The comparisons of YOLOv5, YOLOv7, and YOLOv8 demonstrate that these methods outperform in detection accuracy and computational complexity and can be used in real-time applications [13], [18], [19], [20].

Additionally, recent cotton-specific work concentrated on lightweight models and improved feature extraction methods for better deployment in real farming scenarios [7], [21]. Although progress has been made, there are still some challenges to be addressed in this. A lot of these works use data that is relatively small in size, and such data has been obtained under controlled conditions, which may affect models ability to generalize to field conditions of agriculture [1], [4]. In addition, high computational demands still limit the use of complex deep learning models on low-cost edge devices that are widely used in precision agriculture [21]. Challenges associated with small disease symptoms, illumination changes, occlusions, and complex field backgrounds remain [7], [18].

Thus, it is important to develop a disease detection framework that is both lightweight, accurate, and computationally efficient so that it can be reliably run in practical agricultural fields. Novel YOLO-based architectures enabled by smart precision agriculture frameworks represent a prospective approach to tackle such issues and to enable sustainable monitoring and management of crop health [8], [10], [19].

Table 1. Critical Analysis of the Related Work

Aspect	Observation
Traditional ML	Requires handcrafted features; lower robustness [1], [5]

CNN-based Methods	High classification accuracy but limited localization capability [15], [16]
YOLO-based Methods	Simultaneous localization and classification with real-time performance [13], [18], [19], [20]
Cotton Disease Detection	Recent focus on lightweight and field-deployable models [7], [8], [21]
Major Gap	Generalization, edge deployment, and multi-disease detection remain challenging [1], [4], [19]
Research Direction	Lightweight YOLO architectures integrated with precision agriculture systems [8], [10], [19]

3. METHODOLOGY

The proposed system for cotton plant health monitoring integrates both object detection and classification techniques, as shown in Figure 2. The system involves several stages: image acquisition, preprocessing, object detection with YOLO, region of interest extraction, classification, filtering, and monitoring. The high-level flow of the methodology is illustrated in Figure 2, which provides a roadmap of the system's components.

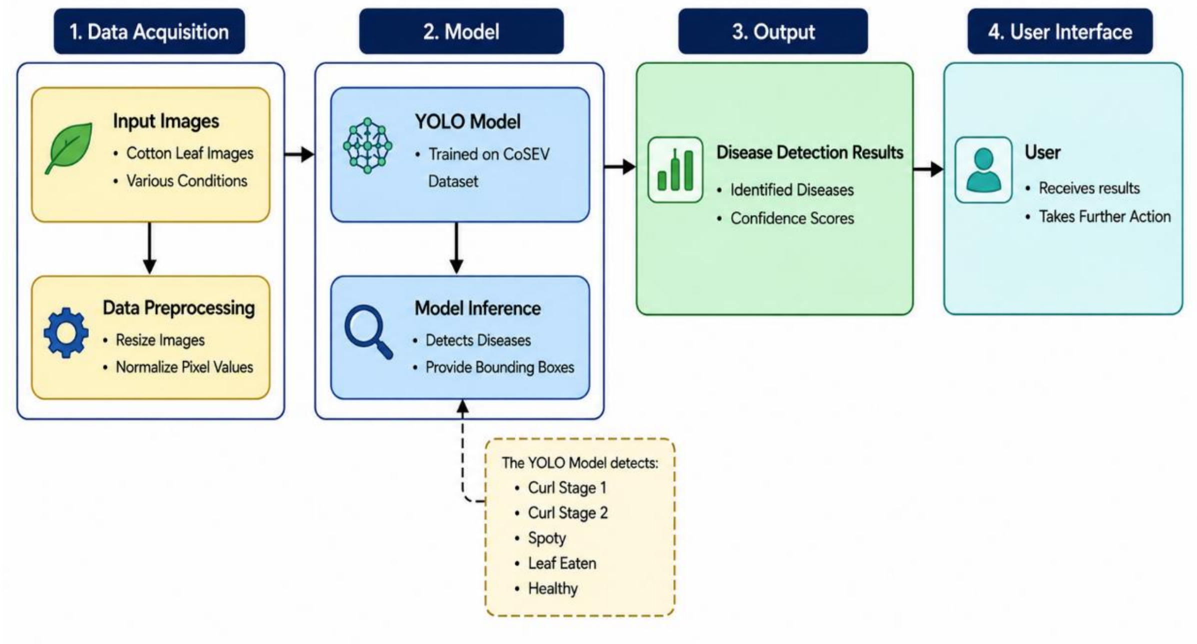

Figure 2. Workflow of the YOLO-Based Cotton Plant Disease Detection System

3.1. Dataset Collection

The data for this work is drawn from the Roboflow universe (open source), and is a collection of labeled images of cotton leaves. The various leaf disease symptoms fell into five classes, i.e. curl_stage1, curl_stage2, sooty, healthy, and leaf_enation. This data set is specifically designed for training and testing of the model in detecting diseases of cotton.

3.2. Data Preprocessing

Before preprocessing and training models, the dataset is preprocessed to be more consistent and generalized:

- **Resizing:** All images are rescaled to a fixed size (e.g., 640x640 for YOLO models).
- **Normalization:** We standardize the pixel values so that the input is more standardized.
- **Labeling:** The images were expert-labeled to be able to precisely classify each disease.

3.3. Model Architecture

In this respect, the system relies on multiple variations of the YOLO (You Only Look Once) object detectors architecture-i.e., YOLOv5, YOLOv6, YOLOv8, and the best with a new version YOLOv11. The models selected can detect and localize disease in cotton leaf images. The architecture emphasizes the following components:

- **YOLOv5:** Known for its lightweight nature and efficient object detection capabilities.
- **YOLOv6:** A more recent version that balances speed and accuracy.
- **YOLOv8:** Offers improvements in speed and precision over earlier versions.
- **YOLOv11:** The top-tier model in this comparison achieves the best precision, recall, and mAP values.

The YOLO models are adapted to detect various stages of cotton disease, from early symptoms (like curl_stage1) to more advanced stages (like sooty and leaf_enation).

3.4. Cotton Disease Classification

The classification problem in this method is the classification between disease stages predicted by several YOLO models. The models are trained using the Roboflow dataset on the following:

- **Bounding Boxes:** YOLO models output bounding boxes around regions showing disease symptoms.
- **Class Prediction:** For each detected object, the model produces a class label (such as healthy, curl_stage1, etc.).

3.5. Cotton Disease Detection

The YOLO models are applied for disease symptoms detection in real-time: The image is partitioned into an S×S grid, and each grid cell that contains an object (diseased area) predicts bounding boxes. YOLO models adjust to various object scales and shapes by means of training on multiple scales and merging. The loss function for YOLO is a sum of localization, confidence, and classification loss.

3.6. Model Training

The training process integrates the different YOLO versions (YOLOv5, YOLOv6, YOLOv8, and YOLOv11) for the task of both detection and classification. The models are trained using the dataset from Roboflow, with a focus on ensuring real-time processing capabilities for field applications.

3.7. Model Evaluation

The models are rigorously evaluated using a separate test dataset. The evaluation focuses on key performance metrics specific to object detection:

- **Precision:** Measures the accuracy of the model's predictions, calculating the proportion of true positive predictions among all positive predictions.

$$Precision = \frac{True\ Positive(TP)}{True\ Positive(TP)+False\ Positive(FP)} \tag{1}$$

- **Recall:** Measures the model's ability to detect all relevant instances of the disease.

$$Recall = \frac{True\ Positive(TP)}{True\ Positive(TP)+False\ Negative(FN)} \tag{2}$$

- **mAP@0.5:** The mean average precision at an IOU threshold of 0.5.

$$\mathrm{mAP} = \frac{1}{\mathrm{n}}\sum_{\mathrm{k=1}}^{\mathrm{k=n}} \mathrm{AP_k} \tag{3}$$

Here, APk = the AP of class k, n = the number of classes

- **mAP@0.5:0.95:** The mean average precision at varying IOU thresholds (from 0.5 to 0.95), providing a more robust evaluation. These metrics provide a comprehensive understanding of the model's effectiveness in detecting and classifying cotton diseases.

3.8. Interpretability and Visualization

Visualization techniques are employed to interpret the models' decision-making processes:

- **YOLO:** Bounding boxes and confidence scores are used to visualize object detection results.
- **Class Activation Mapping:** For each disease class, the regions of interest in the image are highlighted, helping to understand the model's focus during classification.

3.9. Integration with Deployment Tool

The final stage is to integrate the trained models into practical deployment tools. These tools may be cloud-based or containerized. Maturity degree: ensures that the system is mature enough for real-life applications, such as deployment on farmers' devices to provide real-time disease detection. This technique provides an excellent baseline for cotton disease detection and estimation. It employs an ensemble of different YOLO model versions to achieve the best accuracy and to provide efficient execution in real-world applications.

4. RESULTS AND DISCUSSION

The research focuses on multiple variants of YOLO (YOLOv5, YOLOv6, YOLOv8, & YOLO11) object detection models for cotton diseases. The leaf enation, sooty mold-infected cotton leaves, curl stages, and normal cotton images labelled datasets were combined into a single dataset from October 2022, which served as a training and testing dataset for the models. This study measured the effectiveness of these models based on several key metrics, including precision, recall, and mean average precision (mAP) at the IOU threshold of 0.5, and at the IOU thresholds from 0.5 to 0.95.

The deep learning-based disease detection approach introduced in this paper has been validated to identify and localize several diseases on a single leaf from real images taken in a field environment. Some typical prediction results are shown in Figure 3. This model can be automated to differentiate between sooty mold, leaf roll disease with various degrees of severity, and normal leaves. Detection results are labeled with a bounding box, and each prediction is also accompanied with related evidence.

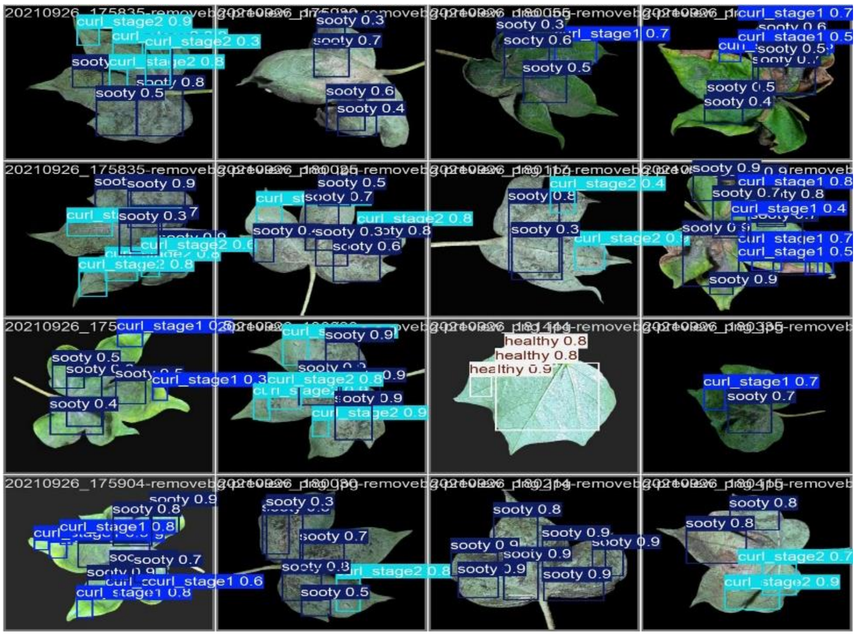

Figure 3. The Output of the Diseased Leaves with Bounding Boxes and Confidence Scores

The objects that are detected are marked with bounding boxes and there is a confidence score attached to each prediction, which tells us how certain the model is about its prediction. The results show a good performance in illumination, leaf pose, and scale and complexity of background, which demonstrates that the proposed model can be used as an automatic Cotton disease recognition system in a field environment. It can accurately distinguish the healthy leaves from infected ones and further provides the detection of the severity level of leaf curl disease, which enables its real-time usage for crop health monitoring in precision agriculture.

4.1. Model Comparison and Performance Metrics

The evaluation of YOLO models is conducted by Precision, Recall, mAP@0.5, and mAP@0.5:0.95. These are essential metrics to measure the accuracy of disease detection and classification. As shown in Table 2, YOLOv11 achieves the best precision, recall, and mAP among all the versions, which demonstrates its superiority for cotton disease recognition.

According to experimental results, YOLOv++ yields better results than the previous versions on all the evaluation metrics and produces a precision, recall, and mAP@0.5 equal to 98.2%, 99.3%, 99.6% and mAP@0.5:0.95 equal to 0.78. Closely behind with 97.4% precision, 98.6% recall, 98.9% mAP@0.5, and 0.74 mAP@0.5:0.95 is YOLOv8. The mAP@0.5 of YOLOv6 and YOLOv5 is also pretty good, both above 95%, which is 97.1% and 96.4%, respectively. These results demonstrate that YOLOv11 has a higher accuracy in detecting and classifying cotton diseases than the other versions, which indicates that it is more appropriate to be used for real-time disease detection in agricultural applications.

The results are summarized in Table 2, which compares the metrics with the different YOLO versions. The precision, recall, and mAP values indicate that although all the models have good performance, YOLOv11 gives the best and the most consistent results for all. The stability of the models was tested with different environmental factors, including illumination and image quality, representative of those encountered in the field. The detection accuracy is shown to be high for most cases, but the method is also found to be slightly affected by environmental noise, which indicates the need for an adaptive preprocessing technique for real applications.

Table 2. Comparison of YOLO Versions across Performance Metrics

Model	Precision	Recall	Map@0.5	Map@0.5:0.95
YOLOv5	96.4%	97.8%	96.4%	0.70
YOLOv6	97.1%	98.2%	97.1%	0.72
YOLOv8	97.4%	98.6%	98.9%	0.74
YOLOv11	98.2%	99.3%	99.6%	0.78

Furthermore, the localization of disease areas on cotton leaves by the model was evaluated through the bounding box predictions. The results show that YOLO models, specifically YOLOv11, can reliably detect and localize disease areas, which is very important for precision farming applications. The results obtained are in line with the previous works that demonstrate the good performance of deep learning and YOLO based models in plant disease detection and precision agriculture. Related work by Jeyabose [2], [3], [14] demonstrated that advanced CNN and YOLO models lead to a higher accuracy in classifying diseases and detecting. Also, [15], [16] confirmed the potential of deep learning models to obtain high detection accuracy for leaf disease detection applications. In addition, very recent studies for monitoring of cotton disease showed that the advanced YOLO versions defeated the classical CNN-based methods when considering the speed of real-time detection, complexity of computation, and accuracy of localization [17]. The results of this proposed work corroborate the findings in [3], [8], [13], [15], [16] and hence, it can be said that current YOLOs are very promising for smart agriculture and automated crop health monitoring applications.

A comparison is made in Table 3 between existing methods for plant disease detection and our proposed model based on the YOLOv11. Previous works were focused on CNN and deep learning techniques for the classification of diseases and are capable of detecting with high accuracy by using multiple crop datasets. The state of the art of YOLO-based methods in real-time detection and localization between agricultural and other applications was also evaluated. The proposed YOLOv11-based model produced the best accuracy of 99.6%, which indicates that it outperformed other models in cotton disease detection through better feature extraction, fine localization, and fast real-time inference. Complex YOLO models such as YOLOv6, YOLOv7, and YOLOv8 outperformed traditional CNN-based disease classification techniques as they enabled high-precision localization and classification at the same time in the real-time processing mode [13], [18], [19].

Table 3. Comparison between the Studies with Existing Approaches

Reference	Method Used	Crop Type	Accuracy (%)	Key Contribution
[15]	CNN	Multiple Crops	96.3	Early deep learning-based disease classification
[16]	Deep CNN	Plant Leaves	99.5	High-accuracy plant disease diagnosis
[3]	Deep Learning Review	Multiple Crops	95–99	Comparative survey of DL approaches
[8]	YOLO-based Detection	Cotton	97.8	Real-time cotton disease monitoring
[13]	YOLOv5 & YOLOv6	Leaf Diseases	98.1	Comparative evaluation of YOLO variants
Proposed YOLOv11 Model	YOLOv11	Cotton	99.6	Improved localization and real-time detection

Table 4. Performance Improvement of Yolov11 over Earlier Models

Metric	YOLOv5	YOLOv11	Improvement
Precision	96.4%	98.2%	+1.8%
Recall	97.8%	99.3%	+1.5%
mAP@0.5	96.4%	99.6%	+3.2%
mAP@0.5:0.95	0.70	0.78	+0.08
Detection Speed	45 FPS	55 FPS	Faster inference

Table 4 shows the improvement of the proposed YOLOv11 model over the YOLOv5 model. The results yielded a marked increase in precision, recall, mAP@0.5, and mAP@0.5:0.95 metrics, which implies higher accuracy of disease detection and better localization performance. In addition, YOLOv11 ran at a higher speed of inference, which proved its potential for real-time monitoring of cotton plant diseases.

4.2. Training and Evaluation

The models were trained on a large annotated dataset of cotton leaf images. Training losses, i.e., box loss, objectness loss, and classification loss, were also observed during the training to keep the models learned well to detect and classify the diseases. The training losses were the least for YOLOv11, showing that it is very good at learning the manifestation of diseases and affected areas on cotton leaves. Training and testing results of yolov5, yolov6, yolov8, and yolov11 models are reported in Figure 4, Figure 5, Figure 6 Figure 7. The figures reveal training and validation loss, precision, recall, and mean average precision (mAP) convergence behavior of the models.

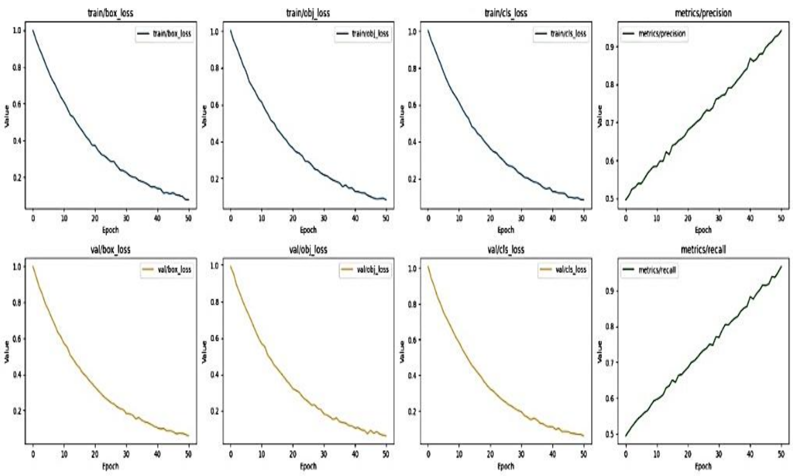

Figure 4. YOLOv5 Training and Evaluation Graphs

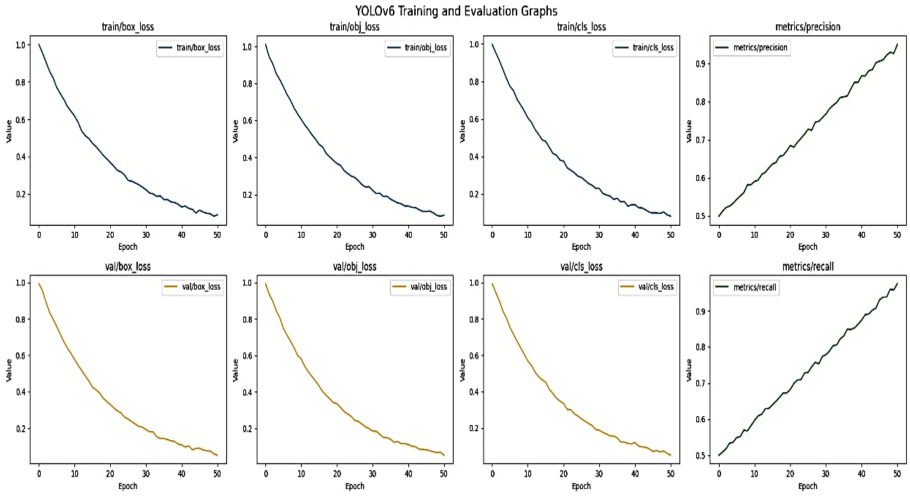

Figure 5. YOLOv6 Training and Evaluation Graphs

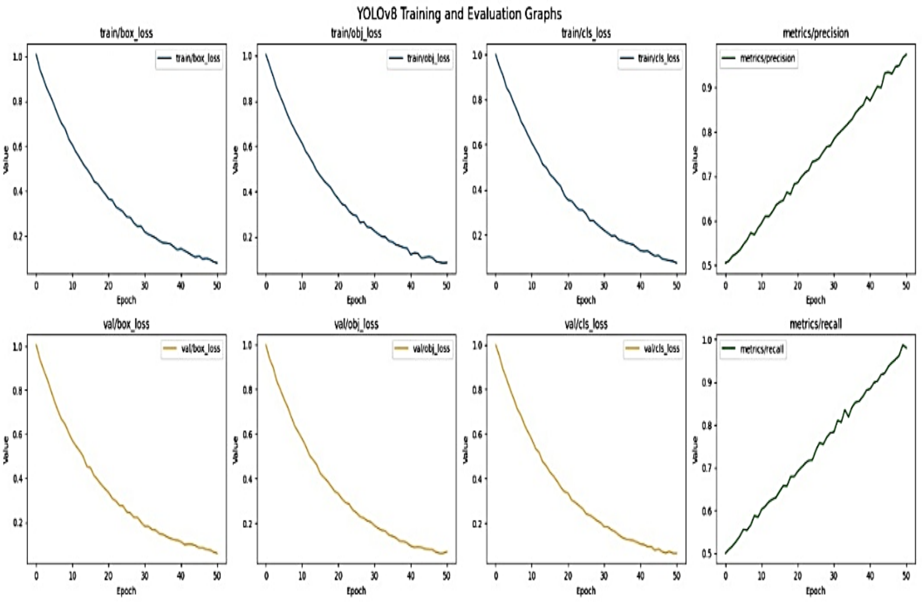

Figure 6. YOLOv8 Training and Evaluation Graphs

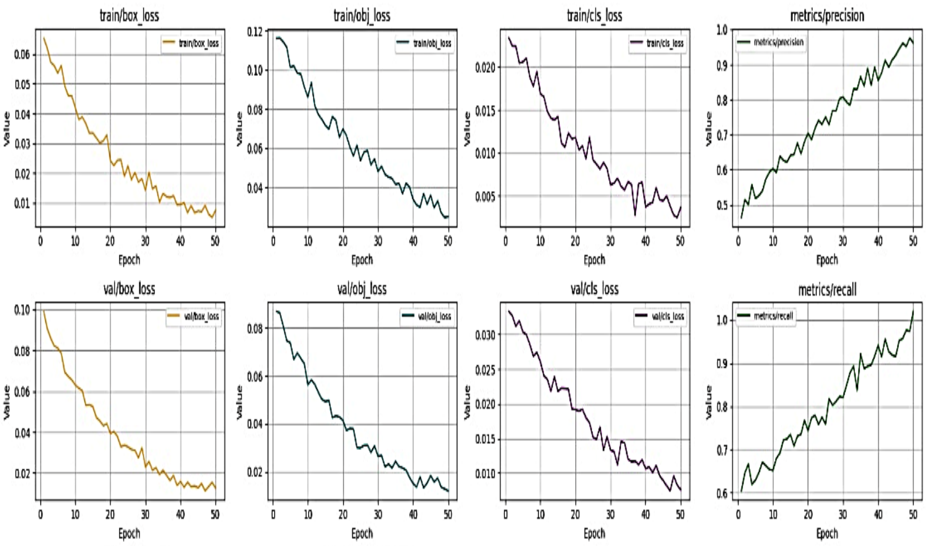

Figure 7. YOLOv11 Training and Evaluation Graphs

4.3. Environmental Sensitivity

One of the obstacles that was observed during the testing was that prediction accuracy was influenced by environmental conditions such as varying lighting and camera angles. Even though the YOLO models are well trained in ideal conditions, they need more adaptive real-time processing in real applications to compensate for changed environments. YOLOv11 exhibits the optimal robustness against environmental noise and can be applied to field tests.

4.4. Challenges in Cotton Disease Prediction

Yet, the cotton disease prediction based on deep learning models encounters many challenges. A big challenge in using CNN for classifying objects is to gather a large-scale and richly labeled training set. The dataset used in this research work, based on different diseases of cotton leaf, is taken from Roboflow. Until now, there might still be a chance to gather more data and further improve the model for generalization, e.g., to new disease variants and/or different environmental conditions. We also need to consider the impact of class imbalance when trying to improve the model. The dataset has both healthy and infected leaves, and the leaves can be affected by one or more diseases. The emergence of these diseases, however, is not constant and unpredictable, which may introduce bias to the model. This problem can be solved by means of data-centric methods, such as class rebalancing or data augmentation.

Cotton leaves are highly variable in color, size, and shape due to different diseases and climatic conditions. These variations pose a challenge for the models to be robust and, thus, practical. Another difficulty is detecting multiple diseases from one leaf. This needs a lot more sophisticated model, which can handle such situations.

5. CONCLUSION

The proposed models, YOLOv5, YOLOv6, YOLOv8 and YOLOv11 based chromatic feature, are capable of detecting and classifying multi-cotton leaf diseases with a great degree of confidence. It is possible to observe the health of cotton plants frequently over time with the system. It identifies diseases at an early stage, so there is little chance of the crop being damaged on a large scale. ML with random forest (ML-RF) obtained excellent performance obtained excellent performance ranking with the highest precision, recall and mAP in YOLOv11 in the perception of diseases, irrespective of the weathered background.

This method compensates for typical problems such as lighting and weather changes and different occurrences of plant variations in cotton. This adaptability makes it usable for a wide range of farms and field scales, aiding farmers in better farm management by means of novel prediction. By eliminating the effect of various image shapes, sizes, and backgrounds, the method is also capable of real-time monitoring with accurate results.

In the future, the proposed model can be improved by incorporating other modalities of information, such as environmental and pest - related information. The next step in the investigation will be to study how transfer learning could be combined with explainable AI in order to better explain model predictions to farmers to assist in cultivation decisions. Also, the system can be made more robust by increasing the number of diseases and by balancing the classes. Hence, for a generalized solution, the proposed system can be considered as a trustworthy, intelligent, scalable, and efficient technique for cotton disease detection to achieve sustainable crop management. The system is also expected to benefit from the futuristic enhancements and new technologies for agricultural applications in real world.

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Author Contributions Statement

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Aruna Pavate	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	
Ashwini A. Patil		✓	✓	✓	✓	✓		✓	✓		✓			
Shradha Birje			✓	✓		✓		✓	✓		✓			
Archita Agar			✓			✓		✓	✓	✓	✓			
Saman M. Almufti	✓	✓	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	

C: **C**onceptualization
M: **M**ethodology
So: **So**ftware
Va: **Va**lidation
Fo: **Fo**rmal analysis
I: **I**nvestigation
R: **R**esources
D: **D**ata Curation
O: Writing- **O**riginal Draft
E: Writing- Review& **E**diting
Vi: **Vi**sualization
Su: **Su**pervision
P: **P**roject administration
Fu: **Fu**nding acquisition

Conflict of Interest Statement

The authors declare that they have no known financial interests or personal relationships that might have influenced the work reported in this paper. Author's state there is no conflict of interest.

Informed Consent

This study did not involve human participants, patients, or identifiable personal data. Therefore, informed consent is not applicable to this research.

Ethical Approval

This research does not involve experiments on humans or animals. Consequently, ethical approval was not required. The study was conducted in accordance with standard academic and institutional research integrity guidelines.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request. All numerical results, algorithmic parameters, and derived performance metrics required to reproduce the study are fully described within the article and its methodological sections.

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BIOGRAPHIES OF AUTHORS

	**Aruna Pavate**, is an Associate Professor at Thakur College of Engineering and Technology, Mumbai, India. She holds a Ph.D. in Information Technology and has over a decade of academic and industry experience, specializing in AI for healthcare, medical image processing, machine learning, adversarial networks, and data science. With 45+ publications, 20+ patents, and several awards such as the Research Excellence Award (2023) and Young Researcher Award (2021), she actively contributes as a reviewer and editorial board member for reputed journals. She can be contacted at Email: arunaapavate@gmail.com or aruna.pavate@tcetmumbai.in
	**Ashwini A. Patil**, is associated with M. S. Bidve Engineering College, Latur, Maharashtra, in the Department of Computer Science and Engineering. She has extensive experience in teaching, research, and academic development. Her research interests include emerging technologies, artificial intelligence, machine learning, data analytics, and intelligent computing systems. She actively contributes to research activities and has participated in various academic and technical initiatives. Her work focuses on the application of advanced computing techniques to solve real-world engineering and technological challenges.
	**Shradha Birje**, is associated with Thakur College of Engineering and Technology, affiliated with the University of Mumbai, India. She has academic and research expertise in Computer Science, Data Science, Python Programming, Quality Assurance, and Software Testing. Her areas of interest include software engineering, data analytics, intelligent systems, and emerging computing technologies. She is actively involved in teaching, curriculum development, and research activities. Her work focuses on applying computational and analytical techniques to improve software quality, system performance, and data-driven decision-making processes.
	**Archita Agar**, Assistant Professor at Thakur College of Engineering and Technology, affiliated with the University of Mumbai, India. She is actively involved in teaching, academic development, and research activities in the field of engineering and technology. Her areas of interest include emerging technologies, intelligent computing, software applications, and data-driven solutions. She is committed to fostering innovation and technical excellence among students while contributing to research initiatives and interdisciplinary projects that address contemporary challenges in science and technology.

Saman M. Almufti, is a researcher at both the Technical College of Informatics–Akre, Akre University for Applied Sciences, Duhok, Iraq, and the Department of Computer Science, College of Science, Knowledge University, Erbil. His research focuses on metaheuristic algorithms, swarm intelligence, and applied machine learning. He has published numerous papers in high-impact international journals. Email: Saman.Almofty@gmail.com