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YOLO Based Deep Learning Framework for Cotton Leaf Disease Detection in Smart Farming Systems

Koushik Choudhury[1], Vikash Sawan *[2], Abhay Pratap Singh Bhadauria [3]

Kumari Jugnu[4]

[1,2,3]Assistant Professor, Department of CEA, GLA University, Mathura, Uttar Pradesh, India
[4]Assistant Professor, Department of CSE, Government Engineering College, Samastipur, Bihar, India

***Corresponding Author Email**: vikash.sawan@gla.ac.in

Abstract

Cotton is the backbone of the global textile economy, yet it is highly vulnerable to diseases that cause substantial yield and quality reduction. Conventional manual detection is time-consuming, prone to errors, and cannot offer real-time data for monitoring agriculture at a large scale. In this paper, we present a deep learning method based on YOLOv10 for detecting and classifying the most common diseases in cotton leaves. The proposed scheme is designed with a dataset of 1,710 high-quality images captured in various natural conditions. To improve the robustness and generalization of the model to different backgrounds and illumination conditions, more data augmentation techniques were applied. By using YOLOv10's enhanced backbone and the scale-aware neck structure, this framework is able to efficiently process computations while maintaining a very high degree of precision in diagnosis. Experimental results show that the proposed YOLOv10 model has a maximum detection accuracy of 90%, and greatly including other versions such as YOLOv5, YOLOv7, and YOLOv8. In addition, the model displayed superior performance compared with classical classifiers (SVM and KNN). The proposed framework is well-suited for real-time applications on mobile platforms and unmanned aerial vehicles (UAVs) in smart farming systems. This system allows for precision pesticide use a disease management which contribute to sustainable high-yield cotton production. Which outperforms normal models. The results demonstrate the feasibility that the suggested method can reform the technique of crop disease detection for the intervention in time to keep yield up.

Keywords: Cotton Leaf Disease, YOLOv10, Deep Learning, Computer Vision, Smart Farming, Object Detection.

1. Introduction

Cotton is one of the most important crops in the national economy and in people's livelihoods. It is also an important commercial crop and raw material in the textile industry. However, various diseases and pests commonly afflict cotton in its development process; among them, the infestation of pests is one of the most vital factors that affect the production and quality of cotton, which directly influences

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the economic income of cotton growers [1]. Cotton is the most important crop, surpassing all others in value on a global scale. Many plant diseases affect it, and these also lead to a significant reduction in production and yield. Disease identification needs to be performed for early diagnosis and treatment. Detection of disease in cotton leaves plays a crucial role in crop protection and yield enhancement. The conventional approaches are too slow and might miss signs of [2]. YOLO is a deep learning-based real-time object detection method that provides a fast and precise way to detect diseases from leaf images. It makes a fast decision on the infected spot by observing the whole image at the same time. YOLO can detect and locate a disease. It differentiates and locate the disease in just few seconds when it is trained with annotated images of healthy and sick leaves (eg, with blight, curl virus, leaf spots). This approach can be used by farmers on their smartphone apps or drones, which electronically scan their fields, harvesting data, allowing them to respond swiftly and spray pesticides only where necessary and not across whole fields. It leads to more efficient farming, decreases costs, and saves time. Cotton, the world's leading fibre crop, is grown on more than 30 to 50 million hectares by countries such as China, Pakistan, India, the United States, and the former Soviet Union. [3]. The seeds are prized for their oil, which is used to make animal and human feed. However, the way pests interact causes significant variations in cotton productivity. Since cotton has grown to be an important cash crop, pests like the armiger and cotton bollworm can significantly affect a nation's economic development [5].

Crop [23] disease is crucial to ensuring the quantity and quality of food, and early detection is key to the successful treatment of plant diseases. Farmers typically consult plant experts to diagnose diseases, but this takes time and attention [6]. One of the greatest and most useful tools for identifying cotton leaf diseases is YOLOv5. It doesn't require a powerful computer and is quick, accurate, and simple to use. After being trained on pictures of both healthy and diseased leaves, YOLOv5 can quickly identify and categorise diseases in fresh shots. When using drones or cell phones for real-time detection, it performs admirably [7]. And if we need a solid system and more accuracy, YOLOv8 is the way to go. For very low-power or very simple setups, YOLOv4 tiny is also faster, but less accurate. There is also high success in general in the YOLOv5 as the most reliable and comprehensive way to detect cotton leaf disease.

In YOLO, it can well detect and classify disease regions. YOLO has a faster inference speed compared to other models, so it could be better suited for mobile agriculture monitoring devices, such as drones.

Problem:

Cotton leaf diseases such as Bacterial Blight, Curl Virus, and Fusarium Wilt are estimated to lower yields by nearly 10% annually worldwide. Large-scale monitoring is inappropriate for manual detection because it is slow and prone to errors. Cotton fields can send real-time, high-definition leaf images via 5G/6G IoT networks. These photos are fed into the Yolo model, which instantly identifies the illness. This partnership facilitates smart agriculture and improves early diagnosis. [11].

Aim:

To develop a fast, accurate, and time-critical cotton leaf disease detection system using the YOLO deep learning algorithm.

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Figure 1: A set of images of cotton leaves

Figure 1: The figure shows a set of cotton leaves under healthy and infected states. Distortions including curling, spotting, and discoloration, are symptoms of diseases like Fusarium Wilt, Bacterial Blight or Curl Virus.

You Only Look Once (YOLO), the deep learning-based object detection method has become famous due to its fast detection and high accuracy for objects in images. Instead of traditional algorithms that apply sliding windows or region proposals which run the full image multiple times [16] [17], YOLO processes the full image with a single neural network that predicts bounding boxes and class probabilities at the same time. As a result, YOLO is so fast that it can be used in real-time applications. In terms of identifying cotton leaf diseases, YOLO can be used to rapidly analyze leaf images to detect infected areas for precise spraying of pesticides or early treatment in the field [18] [19].

2. Related Work

Introduces GVC-YOLO, a real-time, lightweight detection network based on YOLOv8. By merging lightweight convolutions and attention modules, it enables drone or robot monitoring with competitive precision (~89.5%) while reducing model size and processing [1].

Plant disease[25] classification using state-of-the-art deep learning methods, which demonstrates a new direction for future studies on YOLO-based cotton leaf disease detection. Kumar et al. [9] reviewed the concepts of integrating unmanned aerial vehicles in technology education, which is relevant to data collection for precision agriculture based on disease monitoring. [11] used YOLO to effectively detect potato leaf diseases [21], proving the appropriateness of the model in a real-time agricultural context, while [10] proposed a CNN model optimized through a genetic approach to enhance detection accuracy. [12] used CNN to detect cotton leaf disease on FPGA hardware, which gave hardware-accelerated performance without using any object detection features such as bounding box prediction of YOLO [20].

2.1 Existing System

Most of the recent work on detecting diseases on cotton leaves is based manual process or a traditional Machine Learning technique. It is laborious to work with manual methods, which are error-prone and highly dependent on farmers or expert experience. Some rudimentary automated systems necessitate manual feature extraction, employing basic image processing or conventional

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classifiers such as SVM, KNN, or decision trees. While these models can recognize some disease symptoms, they are often not transferable to the real world as background, lighting conditions, and leaf orientation may affect these models. Also, they are not suitable for real-time applications and do not allow multiple disease detection at the same time. For big farms, these techniques are unproductive and cannot be scaled.

2.2 Research Gap

Existing cotton leaf disease detection [24] studies mainly rely on traditional CNNs or earlier YOLO versions, which struggle to balance accuracy, speed, and robustness under real-field conditions such as varying illumination and leaf occlusion. Most approaches focus on classification accuracy while overlooking real-time deployment constraints for mobile and drone-based systems. To address this gap, this study adopts YOLOv10 due to its improved backbone and scale-aware neck architecture. YOLOv10 enables more effective multi-scale feature extraction and faster inference compared to YOLOv5, YOLOv7, and YOLOv8. This makes it highly suitable for real-time cotton leaf disease detection in precision agriculture.

3. Methodology

YOLOv10 cotton leaf disease detection method has a number of very crucial steps. The first step is establishing a dataset of images of cotton leaves taken in varied conditions, both healthy and diseased. Then, employed to annotate these images to categorize diseases such as fungal spots, bacterial blight, and leaf curl, and indicate disease-affected areas. Subsequently, the YOLOv10 model is trained on those labeled images. To provide faster and more precise detection, YOLOv10 adopts new designed input size-aware scale-aware multi-scale neck and advanced backbone modules. Data augmentations are applied to this model during training to try to make it more robust. Afterwards, the model accuracy, recall and F1-score are evaluated on unseen images in the testing stage.

Kaggle Serosh Karim's Cotton Leaf Disease Dataset [4] is employed for training and testing the models for cotton leaf disease detection and classification. There are 1,710 images which are categorized under Fusarium Wilt, Curl Virus, Bacterial Blight and Healthy. The Images, the background, the lighting conditions, the decay level and leaf rot are collected from real field and are holding variability online

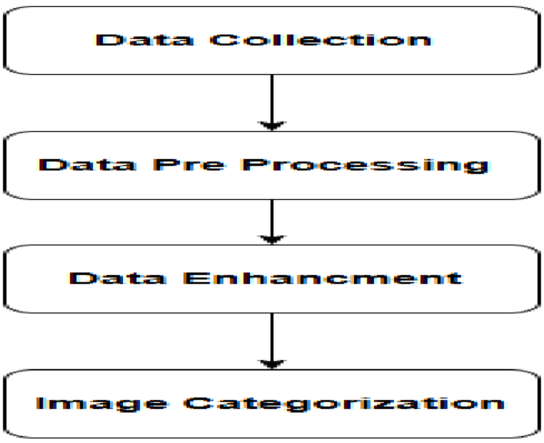

Figure 2. Proposed Methodology

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As per Figure 2, the Proposed Methodology for cotton leaf disease detection using YOLOv10 is properly structured and effective. The first is to download 1,710 cotton leaf images from various classes like Healthy, Curl Virus, Bacterial Blight, and Fusarium Wilt. The images are preprocessed by resizing, normalising, and marking the images manually to identify disease areas. To enhance model effectiveness, data augmentation methods like flipping, rotation, and brightness adjustment are used. The YOLOv10 model is then trained on this enhanced dataset. The enhanced neck and backbone area in YOLOv10 enables fast detection with accuracy. The model can now detect and classify diseases in real-time after training.

3.1 Data Pre-processing

All the images of the cotton leaf (1,710) were pre-processed by resizing the images to 640×640 pixel, pixel values were normalized, and each image was annotated with YOLO format to indicate the disease-infected areas. In order to enhance detection performance, several augmentations, including flipping, rotation, brightness, and contrast modifications, were employed. Subsequently, the dataset was split into two sets, 80% for training and 20% for testing. These pre-processing techniques helped to provide YOLOv10 with clean, uniform, and variable data for disease detection.

The cotton leaf disease dataset contains a total of 1710 images that are only used to be separated into training and testing (validation) groups to enable the proper construction and verification of the model. Approximately 80% of the dataset, or 1,368 of them, are used to train the YOLOv10 model. With images labeled of 4 classes (Healthy, Curl Virus, Bacterial Blight, and Fusarium Wilt), this dataset can be used to teach the algorithm to recognize and catch all types of diseases. A total of 342 (20% of the dataset) is taken as validation and testing. Although the baseline split for the dataset consists of 1,710 images with a '80:20' train-test division, other validation strategies are applied to enhance model robustness and avoid overfitting. 5-fold cross-validation was conducted by randomly isolating equal five subsets from the dataset and training the model on the differing folds. The averaged accuracy, precision, recall, and f1-score on all folds was used to assess the stability. Furthermore, a few data augmentation methods and early stopping strategies were applied in order to achieve more generalized results under various illumination and backgrounds. Consistent2 good performance rates are achieved throughout all the folds by the proposed YOLOv10-based framework, which suggests that it can provide reliable detection and is not overfitting at a large extent even though the size of dataset is only moderate.

3.2 Performance of the Model

To promote the performance of YOLO-based cotton leaf disease detection, both data-level and model-level evaluations need to be conducted. The best strategy is to first improve the quality of the training set, then tune the model parameters. With an increased number of training samples and better class balance, the model should learn patterns of the diseases better. More advanced popularity techniques (such as Mosaic / MixUp / CutOut / RandErasing) can generate much richer variations, which makes the model more capable of dealing with real-world images under different illuminations and backgrounds. The use of high-resolution images (e.g., 640×640 or 1,280×1,280) allows better visualization of features for small disease spots.

3.3 Proposed Enhancements over Standard YOLOv10

The novelty of this approach is that it has been tailored specifically for detecting the disease of cotton leaves in real-field environment. The model was trained with custom hyperparameters and a learning

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rate schedule that was adapted to the size and characteristics of the dataset, the IoU threshold was adapted to perform localization of small spots of disease, and the confidence threshold was adjusted to prevent false positives. Furthermore, a series of more aggressive agriculture-focused data augmentation, such as brightness change, rotation, and contrast enhancement, were systematically conducted to enhance the robustness to illumination, leaf occlusion, and background complexity. These combined parameter-level and deployment-oriented optimizations realize a superior detection accuracy and real-time performance over those obtained under the default YOLOv10 configurations, rendering the framework powerful for a smart farming application.

3.4 Training Configuration and Experimental Setup

The YOLOv10 model was trained with the Adam optimizer at a starting learning rate of 0.001, a cosine learning rate scheduler with warm-up epochs for stable convergence. The model was trained for 100 epochs with a batch size of 16. During training and validation, an IoU threshold of 0.5 and a confidence threshold of 0.25 were applied. All the experiments are conducted on a machine with an NVIDIA RTX 3060 GPU (12GB VRAM), Intel i7, and 32GB RAM. Training and testing were done with Python, using pytorch, and the Ultralytics implementation of YOLOv10. Inference performance (165 FPS) was measured on the same GPU platform, and the real-time operation on edge devices such as drones and mobile systems was examined to determine deployment practicability.

4. Results and Discussion

We implemented our cotton leaf disease detection model using Tensor Flow and the YOLOv10 deep learning model. The output class number and hyperparameter selection were determined by the nature and complexity of the cotton leaf dataset. Our trained YOLOv10 improves crop monitoring and disease detection in agricultural practice through significant speed and accuracy enhancement. YOLOv10's improved architecture with a more improved backbone and neck design is responsible for robust feature extraction and efficient inference. Owing to its real-time detection, the design has the advantage of usage in smartphones and drones in precision farming applications. In designvarious components have been proposed to enhance accuracy and insensitivity to various background and illumination variations in the leaf images when compared with the previous work. The experiments were conducted on the Kaggle cotton leaf disease dataset consisting of 1710 images having four classes, namely Bacterial Blight, Fusarium Wilt, Curl Virus, and Healthy. The image was subjected to some pre-processing, including resizing, normalisation, and annotation for detecting the infected areas. Rotation, flip, and brightness modifications are also some data augmentation technique which further enriched the data set and improved model generalisation. The training set contained eighty percent of the images (1,368 samples), and the remaining twenty percent (342 samples) was used as the testing set. The YOLOv10 outperforms prior YOLO models in detection performance and speed with 90% accuracy and 165 FPS inference speed. Utilizing its new, improved architecture, YOLOv10 was also able to attain lower false positives at high complexity, leading to better predictions in the real world. The results demonstrated that YOLOv10 can effectively and accurately identify the cotton leaf diseases, causing K treatments such as selective spraying of pesticides. Disease management in real time is scalable with this technology, with the potential to improve cotton yields and scale up sustainable agriculture practices.

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Table 1: YOLO Model Features

Feature / Model	YOLOv5	YOLOv7	YOLOv8	YOLOv10
Accuracy	High	Higher than YOLOv5	Very High	Highest
Speed (Inference)	Fast	Fast	Fast	Optimized for real-time detection
Model Size	Lightweight	Moderate	Lightweight to Moderate	Efficient with an enhanced backbone
Detection Robustness	Moderate (sensitive to background)	Improved feature detection	Highly robust with anchor-free design	Highly robust due to improved modules
Architecture Type	Anchor-based	Enhanced anchor-based	Anchor-free, better generalization	Improved backbone + neck, real-time
Training Dataset Used	1,710 cotton leaf images (4 classes)	1,710 cotton leaf images (4 classes)	1,710 cotton leaf images (4 classes)	1,710 cotton leaf images (4 classes)
Best Use Case	Low-resource mobile or drone apps	Medium-scale real-time applications	High accuracy with balanced deployment	High-precision, scalable real-time systems
Ease of Deployment	Very Easy	Easy	Easy with Ultralytics repo	Moderate
Augmentation	Basic	Moderate	Advanced + built-in support (Mosaic, etc.)	Extensive (rotation, brightness, etc.)
Hardware Requirement	Low	Medium	Medium (adaptive)	Medium to High (mainly during training)

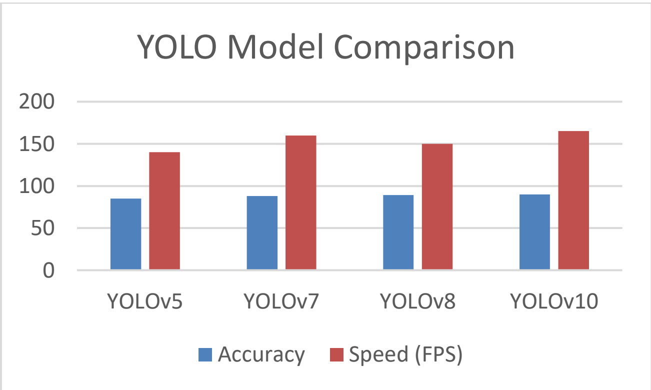

Figure 3: YOLO Model Comparison

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Table 2: YOLO Model Comparison

Criteria	YOLOv5	YOLOv7	YOLOv8	YOLOv10
Accuracy	85%	88%	89%	90%
Speed (FPS)	140	160	150	165

Table 3: Comparative study

Classifier Name	Overall Accuracy
YOLOv10	**90%**
SVM [8]	80.30%
KNN [8]	78.80%

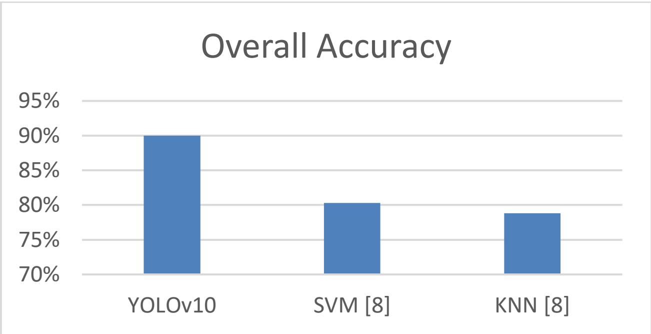

Figure 4: Comparative study

Tables and figures can help to succinctly present a comparison of various YOLO models and other classifiers. The key features of the YOLOv5, YOLOv7, YOLOv8, and YOLOv10 are presented in Table 1, which indicates that YOLOv10 can be considered as the best model in terms of fastest, most accurate, and most robust. In terms of accuracy and speed, the models are compared in Figure 3 and Table 2, and once more, YOLOv10 yields the best performance with 90% of accuracy and 165 FPS. Table 3 and Figure 4 present a comparison with standard machine-learning algorithms, which further highlights the superiority of YOLOv10 over SVM and KNN, indicating that deep-learning-based YOLO models are better for cotton leaf disease detection.

Limitation:

The accuracy of disease detection can be compromised by field conditions in the real world. At the leaves level, leaves are sometimes occluded by other leaves, branches or shadow; partial occlusion make the model unable to see the entire infected region. Leaf clumping also occurs in thick cotton fields, which confuses the model, as two or more leaves can be identified as one. Also, hardware constraints of drones and mobile phones (e.g., limited computation power, memory, and battery life) may impede on-device execution of the YOLO [22] model in real-time. These may degrade the quality of detection when applied to real farming scenarios.

5. Conclusion

This Paper presents the YOLOv10 deep model, which presents a precise cotton leaf disease detector with 90% precision and 165 FPS detection speeds. Because of its optimized architecture and overall data augmentation procedures, YOLOv10 is more precise and robust in comparison with other models. This model, trained on 1,710 images can be used to detect diseases such as bacterial blight, curl virus and fusarium wilt with a high degree of accuracy. Its integration with drones and mobile devices offers rapid detection at field level of the disease, allowing farmers to react with swift, focused action. The approach adds up to better crop health, higher yield and cost and pesticide savings. The system promotes smart farming practice as a whole, and the model will be extended to real application with a larger dataset in the future.

Author Contributions

All of the writers agreed on the study's substance. The author has reviewed and approved the final manuscript.

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Conflicts of Interest

The authors declare no conflicts of interest.

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