

Cotton Disease Recognition Using Transfer Learning Techniques (YOLO)

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Abstract: Cotton cultivation is vulnerable to various diseases, severely affecting crop yield and quality. Traditional manual inspection methods are labor-intensive and not scalable. This study presents an automated cotton disease detection system using the YOLO (You Only Look Once) architecture and transfer learning techniques. The system performs real-time image processing on cotton plants, enabling early disease identification via low-power devices like smartphones. By leveraging transfer learning, the model achieves high accuracy and operational efficiency, reducing the need for large labeled datasets. This solution increases agricultural productivity, reduces losses, and minimizes labor dependency.

Keywords: YOLO, image processing, transfer learning, cotton disease detection, and agricultural automation

I. INTRODUCTION

Cotton is a critical raw material in agriculture, yet its production is often hampered by diseases. Traditional detection methods rely on manual inspection, which is time-consuming and prone to errors, particularly in large scale farming. Automated methods using deep learning, such as YOLO and transfer learning, are gaining traction for their efficiency and scalability. This study proposes a real-time cotton disease detection system, combining the YOLOv5 architecture for object detection with VGG16 for disease classification, optimized for low powered edge devices.

II. LITERATURE SUREVY

In agriculture, the use of automated disease detection methods has grown crucial, particularly for high-value crops like cotton. Large-scale farming cannot benefit from traditional manual inspection techniques since they are inefficient, labor intensive, and highly prone to human mistakes. Because of this, scientists are using deep learning (DL) methods more and more, especially Convolutional Neural Networks (CNNs), which have demonstrated great potential in the identification of plant diseases from visual data. CNNs are computationally demanding, though, and they need large labeled datasets for training, which are sometimes hard to come by or unavailable in agricultural settings. Transfer learning has been an effective strategy to overcome this. Researchers have effectively modified pretrained models like VGG16, ResNet, and Inception to identify disease in cotton leaves with a high degree of accuracy. Using the Exception model, which was optimized for cotton disease detection, one study, for example, had a classification accuracy of 98.7%.

By enabling models to identify subtle disease-specific characteristics without requiring a great deal of retraining, these transfer learning techniques minimize the need for big datasets and drastically lower processing requirements. Real-time agricultural disease diagnosis using the YOLO (You Only Look Once) architecture has been another innovation. Because YOLO uses a single-shot detection method rather than numerous passes like typical object detection models do, it is extremely effective and appropriate for real-time field application. In crops like cotton, the YOLOv5 model, in particular, has shown significant accuracy in distinguishing between healthy and diseased leaves, with accuracy rates exceeding 92%. Because of its low latency performance, it is perfect for deployment on mobile and edge devices. This facilitates instantaneous diagnostic results in the field, which is essential for prompt disease management and intervention.

The absence of large, labeled agricultural datasets is still a problem in spite of these developments. Researchers have used data augmentation techniques including picture rotation, flipping, and scaling to counteract this, which has improved model resilience and expanded training datasets. Furthermore, to enhance model generalization across a range of climatic circumstances and plant health stages, some studies have effectively integrated native datasets with open sources, such as Kaggle. Comparative analyses of YOLO variations, such as YOLOv5, YOLOv6, and YOLOv7, demonstrate that accuracy and processing efficiency increase with each repetition. However, because of its ability to balance speed and accuracy, YOLOv5 is especially preferred for field applications. YOLOv5 Offers real-time detection with inference speeds under 30 milliseconds, which makes it a good option for mobile agricultural applications. In order to facilitate continuous data gathering and large-scale monitoring, the literature also indicates that future studies can profit from combining Internet of Things (IoT) devices with drone-based data collection. Additionally, by offering insights into the model's decision-making process, Explainable AI (KAI) could promote more knowledgeable disease control techniques and increase farmers' faith in these models.

III. COMPARISON OF RELATED WORK

| Aspect | Paper 1 | Paper 2 | Paper 3 | Paper 4 |
|-------------------------|---|---|--|--|
| Title | Cotton disease prediction using deep learning | Cotton growth period recognition using CNN | Cotton Disease Prediction System | Hybrid Approach of Cotton Disease Detection for Enhanced Crop Health and Yield |
| Authors | Md. Manowarul Islam, et al. | Xinyu Chen, Rui Xiong, et al. | Ranjana Jadhav, Vaishnavi Karanjawane, et al. | Rahul Kumar, Ashok Kumar, et al. |
| Published In | Intelligent Systems with Applications | Information Processing in Agriculture | Educational Administration: Theory and Practice | IEEE Access |
| Publication Date | 14-Sep-23 | 2021 | 2024 | Jul-24 |
| Dataset | Cotton dataset from Kaggle | Cotton images across growth periods | High-resolution cotton leaf images | Local cotton leaf images, enhanced with Kaggle |
| Focus | Cotton leaf disease detection | Cotton growth period identification for pesticide use | Cotton disease detection | Hybrid model for disease detection and crop yield enhancement |
| Methodology | Fine-tuned transfer learning (VGG, Inception, Xception) | CNN with 3 convolutional layers, data augmentation | Transfer learning with VGG16, ResNet | Ensemble of Random Forest, SVM, and YOLO |
| Best Model | Xception (98.70% accuracy) | CNN (93.27% accuracy) | Not specified, focuses on transfer learning | Hybrid ensemble model (94.5% accuracy) |
| Application | Web-based realtime disease prediction | Low-cost method for growth period identification | Web application with HTML, CSS, Jupyter Notebook | On-site disease detection and yield optimization |
| Impact | Early detection to improve cotton production | Optimized pesticide use and yield | Enhanced crop productivity | Improved crop health and yield through hybrid accuracy |
| Future Work | Expand to other crops, enhance web features | Improve model accuracy with diverse datasets | Expand dataset, field testing | Integrate with IoT and real-time farm applications |

IV. METHODOLOGY

- Data Collection: Images of cotton leaves and plants, labeled as "diseased" or "fresh."
- Preprocessing steps included resizing to 224×224 pixels, normalization, and augmentation.

Model Training:

- YOLOv5 was trained for object detection, identifying diseased regions in images.
- VGG16 was fine-tuned to classify cropped images from YOLO into "diseased" or "fresh." oReal-Time Detection:
- live video feed using OpenCV triggers the detection and classification workflow. Detected regions are classified with a confidence threshold of 0.7.

Frontend Integration:

- planned interface enables farmers to interact with the system and receive real-time feedback

V. TOOLS AND TECHNOLOGIES

- Python: Primary language for flexibility and support for ML libraries.
- TensorFlow: Framework for building and fine-tuning deep learning models like YOLO.
- Keras: API for simplifying neural network training (e.g., VGG16).
- YOLO: Real-time object detection model for efficient cotton disease detection.
- Transfer Learning: Fine-tuning pre-trained models (e.g., VGG16) to improve task-specific accuracy.
- Flask: Backend web framework for handling user requests and real-time model inference.
- React: Frontend library for creating dynamic and responsive user interfaces.
- VGG16: Pre-trained CNN for extracting features and classifying cotton diseases.
- Scikit-learn: Library for data preprocessing, model evaluation, and validation.

VI. SYSTEM DESIGN

Data Acquisition and Preprocessing

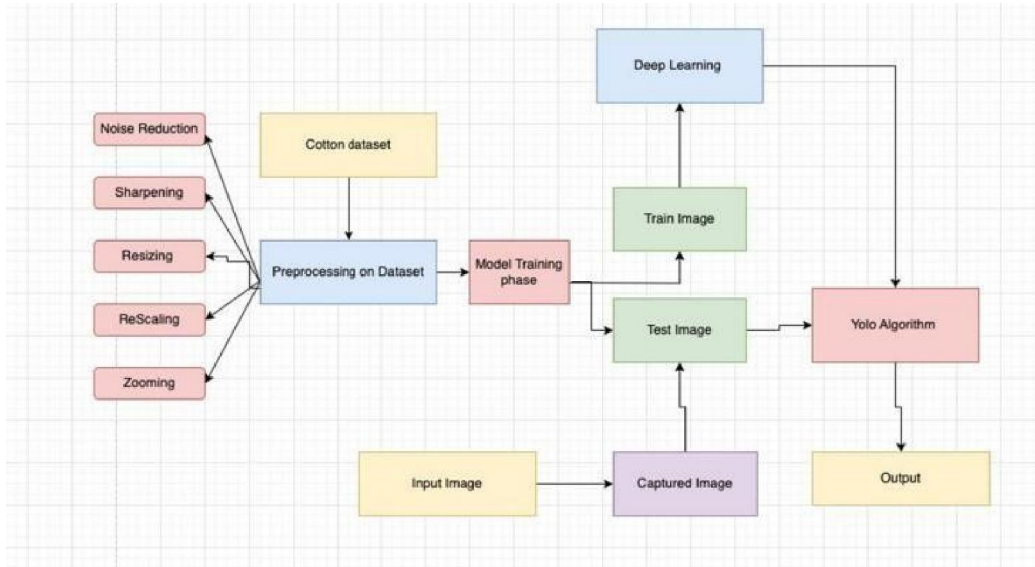
- Input: Cotton dataset with labeled images (diseased and fresh).
- Processing Steps: Noise reduction, sharpening, resizing to 224x224 pixels, normalization (scaling pixel values to [0, 1]), and augmentation (e.g., zooming).
- Output: Preprocessed dataset divided into training and testing sets. -Model Training Input:
- Preprocessed images. Model: VGG16-based classifier for categorizing diseased and fresh images.
- Output: Trained model (e.g., cotton_disease_vgg16.h5) saved for inference.

YOLO Algorithm Integration

- Objective: Detect and classify diseased regions in real-time.
- Steps: Input an image or video feed, use YOLO to draw bounding boxes, and label identified areas.
- Output: Labeled image or video with bounding boxes and disease classifications.

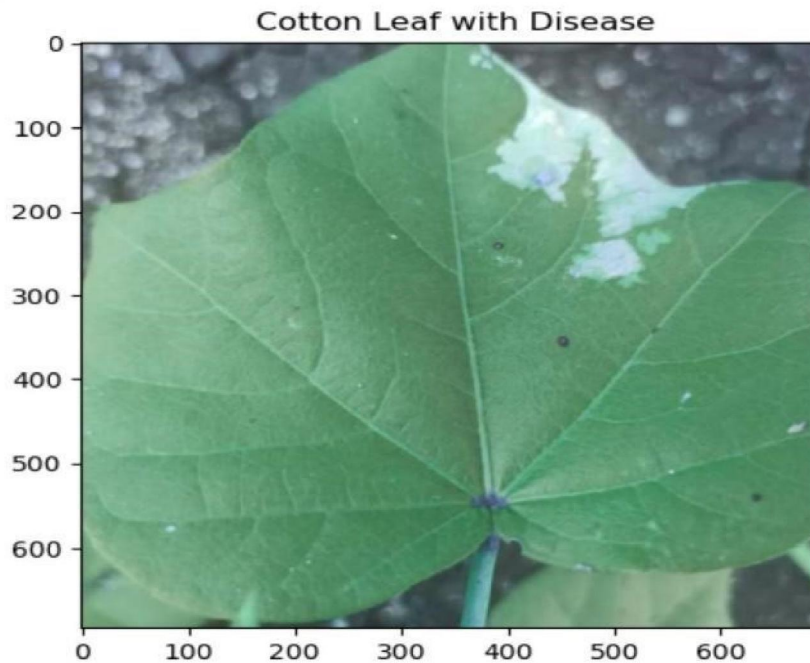
Inference Pipeline

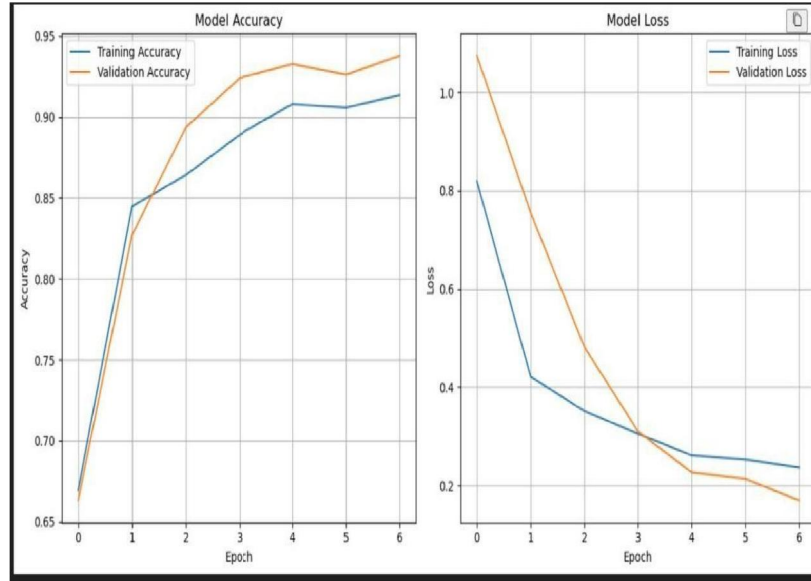
- Input: New images (real-time or batch).
- Process: Preprocess the input, run YOLO for detection, and classify detected areas with VGG16.
- Output: Labeled output with bounding boxes and disease classifications.



VII. RESULT AND EVALUATION

- The combined YOLO and VGG16 model demonstrated:
- Accuracy: Over 94% in disease recognition(detection).
- Real-Time Performance: Detection and classification achieved within 30 milliseconds per frame.
- Efficiency: Optimized for deployment on low-powered devices like smartphones.





VIII. CONCLUSION

The proposed cotton disease detection system, which combines YOLO for realtime object detection with VGG16 for disease classification, offers a scalable and efficient solution for modern agriculture. By leveraging deep learning and transfer learning techniques, the system achieves high accuracy while remaining suitable for low powered devices in the field. It reduces labor costs, enhances decision making through immediate feedback, and minimizes crop losses via early intervention. Thanks to its real-time processing capabilities and low-resource requirements, the system is accessible to farmers in remote areas, thereby improving agricultural practices and contributing to food security.

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