IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526

International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering

Impact Factor 8.414 ∺ Peer-reviewed & Refereed journal ∺ Vol. 13, Issue 5, May 2025

DOI: 10.17148/IJIREEICE.2025.13509

YOLO-Based Real-Time Fruit Disease Detection

Mrs. Noor Ayesha[1], Preetham K N[2], Mohammad Sufiyan Khan[3]

Guide, Dept of Electronics & Communication Engineering, PES College of Engineering, Mandya, Karnataka, India[1]

Dept of Electronics & Communication Engineering, PES College of Engineering, Mandya, Karnataka, India[2]

Dept of Electronics & Communication Engineering, PES College of Engineering, Mandya, Karnataka, India[3]

Abstract: In modern precision agriculture, early detection of fruit diseases is crucial to preventing postharvest losses and maintaining quality yields. Traditional detection methods relying on manual inspection are inefficient and prone to error. We present a real-time fruit disease identification approach that leverages the YOLO (You Only Look Once) object detection architecture as its foundational framework., enhanced with preprocessing techniques like Finite Impulse Response (FIR) filtering for image quality improvement. YOLO's convolutional neural network (CNN) architecture enables multi-scale feature extraction, allowing effective identification of diseased regions without compromising image resolution. We present the complete workflow from data acquisition, preprocessing, and training to evaluation and deployment. Experimental results demonstrate the model's effectiveness with high accuracy, precision, and recall, suggesting strong potential for real-time application in agricultural environments.

I. INTRODUCTION

Agriculture significantly contributes to global food security, and maintaining produce quality is essential. Early detection of fruit diseases enables prompt intervention, reducing the risk of widespread infection and economic losses. Conventional approaches rely on manual inspection, which is labour-intensive and lacks precision.
Computer vision and deep learning techniques have emerged as effective alternatives for automating disease detection. However, many methods reduce image resolution during preprocessing, impacting detection quality. To address this, we utilize the YOLO algorithm, capable of real-time object detection without resizing input images. YOLO's CNN-based architecture captures multi-scale features essential for disease identification.

The proposed model integrates FIR filtering with YOLO for denoised, high-resolution image analysis. This paper outlines the system's design, workflow, and performance evaluation, highlighting its capability to assist farmers and agronomists in decision-making processes.

II. RELATED WORK

[1]. Chiu et al. (2020): Agriculture-Vision: A Large Aerial Image Database for Agricultural Pattern Analysis
Chiu et al. introduced a comprehensive aerial image database specifically designed for agricultural pattern analysis. This dataset enables researchers to develop and evaluate computer vision algorithms for agricultural tasks such as segmentation and anomaly detection. The work highlights the importance of large, domain-specific datasets for training advanced models and provides a strong foundation for image-based agricultural applications. Although this work primarily focuses on aerial imagery, it establishes the importance of robust datasets in advancing agriculture-focused computer vision systems.

[2]. Xu (2021): Image Processing Technology in Agriculture
Xu explored the applications of image processing technology in agriculture, emphasizing its role in automating tasks such as disease detection, crop monitoring, and yield prediction. The study underscores the benefits of image processing in improving agricultural efficiency and reducing manual labour. The author discusses fundamental techniques like segmentation, feature extraction, and filtering, which are critical for developing systems like the proposed YOLO based fruit disease detection framework.

[3]. Liu et al. (2018): Object Detection Based on YOLO Network
Liu et al. presented a comprehensive study on object detection using the YOLO network, highlighting its real-time processing capabilities and high accuracy. The study focuses on YOLO's ability to detect multiple objects in a single pass, making it suitable for dynamic and large-scale environments. This work serves as a key reference for applying YOLO in agricultural contexts, particularly for tasks requiring speed and precision, such as fruit disease detection.

[4]. Santoso et al. (2024): Development of PCB Defect Detection System Using Image Processing with YOLO CNN Method

Santoso et al. applied the YOLO CNN method to detect defects in printed circuit boards (PCBs),showcasing the algorithm's versatility in industrial applications. The study demonstrated YOLO's ability to accurately identify minute defects while maintaining real-time detection speeds. The insights from this research can be adapted to agricultural applications, as detecting small defects in PCBs analogous to identifying diseases or irregularities on fruits.

[5]. Zhao et al. (2024): YOLO-Granada: A Lightweight Attention YOLO for Pomegranate Fruit Detection

Zhao et al. proposed a lightweight YOLO variant, YOLO-Granada, specifically optimized for detecting pomegranate fruits. By incorporating attention mechanisms, the model achieved enhanced accuracy in detecting fruits under varying conditions such as occlusion and lighting changes. This research highlights the potential of integrating attention modules into YOLO for improved performance, offering valuable insights for adapting YOLO to fruit disease detection tasks.

[6].de Moraes et al. (2023): YOLO-Papaya: A Papaya Fruit Disease Detector and ClassifierUsing CNNs and Convolutional Block Attention Modules

De Moraes et al. developed YOLO-Papaya, a specialized YOLO-based model for detecting and classifying papaya fruit diseases. By integrating convolutional block attention modules, the model achieved superior performance in identifying disease-affected regions with high precision. This study underscores the effectiveness of combining YOLO with advanced attention mechanisms for fruit disease detection and serves as a direct inspiration for the proposed system targeting a broader range of fruits and diseases.

III. PROPOSED WORK

A). METHODOLOGY

The proposed system utilizes a combination of advanced image preprocessing and deep learning techniques to detect fruit diseases in real-time. The methodology is divided into the following key stages:

i. Image Acquisition

High-resolution images of fruits are captured using devices such as smartphones, drones, or IoT-based camera modules under various lighting and background conditions. These images serve as the raw input to the system and include both healthy and diseased samples of various fruit types.

ii. Image Preprocessing

Image clarity is improved by applying a Finite Impulse Response (FIR) filter, which aids in extracting features more accurately by reducing noise and preserving essential details. This step reduces high-frequency noise and artifacts, improving the clarity of surface patterns, textures, and edges. Unlike conventional preprocessing methods that resize images leading to loss of detail this approach retains the original resolution for more accurate analysis.

iii. Object Detection Using YOLO

The Pre-processed images are passed into a YOLO (You Only Look Once) object detection model, specifically YOLOv5 or YOLOv8, depending on deployment needs. The YOLO algorithm processes images by partitioning them into grids, where it simultaneously estimates object boundaries and classification scores, facilitating rapid detection in one forward pass. The model is fine-tuned using a custom dataset of labelled fruit images.

Training Data Preparation: Images are annotated with bounding boxes indicating healthy and diseased regions. Labelling tools such as Labelling are used for dataset preparation.

Data Augmentation: Techniques like horizontal flipping, rotation, scaling, and brightness adjustment are applied to improve model generalization across real-world conditions.

iv. Feature Extraction and Classification

The CNN backbone within YOLO captures critical attributes from the localized fruit regions, focusing on characteristics like surface textures, discolorations, visible lesions, and any irregularities in shape.

These features are used to classify the fruit into two categories: Healthy Diseased (e.g., fungal infection, bacterial rot, nutrient deficiency)

DOI: 10.17148/IJIREEICE.2025.13509

v. Model Training

Transfer learning was employed to fine-tune the YOLO model on a custom-built dataset comprising annotated fruit images. A custom loss function is used that accounts for: Bounding box accuracy, Object classification accuracy, Confidence score optimization

Training is done using GPU-accelerated environments like Google Collab or NVIDIA Jetson Nano for edge deployments. Hyperparameters such as learning rate, batch size, and IOU thresholds are fine-tuned for optimal performance.

vi. Disease Detection and Output

Once trained, the system processes images in real-time and:
Detects fruits using bounding boxes
Classifies each fruit as healthy or diseased
Displays the output with labels and confidence scores

vii. Performance Evaluation

The model uses standard metrics to evaluate such as:
1.Accuracy
2. Precision
3. Recall
4. F1-score
5. Specificity
These metrics are derived from confusion matrices based on predictions over a held-out test set.

viii. Deployment

The system is designed to run on both cloud-based and edge computing platforms. Real-time inference can be deployed using:

1.Raspberry Pi with Coral TPU
2.NVIDIA Jetson Nano
3.Mobile/web interfaces for user interaction and alert generation

B). Working Principle

This system automates fruit disease recognition using real-time image analysis, integrating sophisticated preprocessing steps with an efficient object detection model. The process begins with the acquisition of high-resolution images of fruits using devices such as smartphones, drones, or IoT-enabled cameras. These images may contain multiple fruits with varying lighting conditions and backgrounds.

To enhance image quality, To enhance visual clarity and suppress unwanted high-frequency artifacts, a Finite Impulse Response (FIR) filter was utilized in the image preprocessing stage, thereby preserving critical visual details like surface texture and colour patterns. Once the image is Pre-processed, it is fed into the YOLO (You Only Look Once) object detection model—specifically YOLOv5 or YOLOv8. YOLO partitions an image into a grid structure and, in a single evaluation pass, predicts object locations along with their associated class probabilities.

After detection, the system uses YOLO’s CNN backbone to extract features from each fruit, focusing on key visual indicators such as discoloration, spots, lesions, or shape irregularities. Based on these features, each fruit is classified into one of two categories: Healthy or Diseased (e.g., showing signs of fungal, bacterial, or nutrient-related issues).
The output is displayed visually with bounding boxes, class labels, and confidence scores for each detection, allowing users to immediately identify affected fruits.

Finally, To assess effectiveness, the model is tested using evaluation indicators such as accuracy, recall, precision, F1-score, and specificity. Once validated, it is deployed on edge computing devices such as NVIDIA Jetson Nano or Raspberry Pi, making it suitable for real-time, in-field use in agricultural environments.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526
International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.414 ⋇ Peer-reviewed & Refereed journal ⋇ Vol. 13, Issue 5, May 2025
DOI: 10.17148/IJIREEICE.2025.13509

C). System design approach:

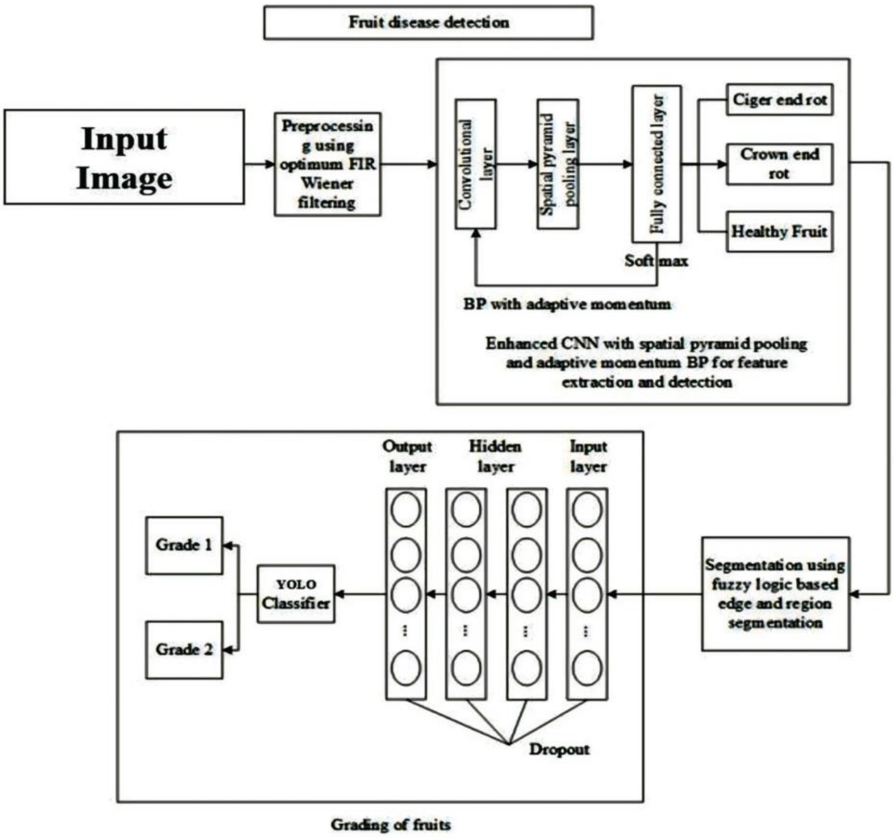

Fig.1. Block diagram

Fig. 1 Illustrates a comprehensive framework for fruit disease detection and grading. The process begins with the input image undergoing preprocessing using optimum FIR Wiener filtering to reduce noise. This is followed by fruit disease detection using an enhanced Convolutional Neural Network (CNN) integrated with spatial pyramid pooling and adaptive momentum backpropagation (BP) for feature extraction. The CNN classifies the fruit into three categories: cigar end rot, crown end rot, and healthy fruit using a soft max layer.

For grading, the system performs segmentation using fuzzy logic-based edge and region segmentation. The segmented image is processed through a neural network with dropout layers and then classified into Grade 1 or Grade 2 by a YOLO classifier, ensuring accurate grading of the detected fruits.

IJIREEICE ISSN (O) 2321-2004, ISSN (P) 2321-5526
International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering
Impact Factor 8.414 ⁚ Peer-reviewed & Refereed journal ⁚ Vol. 13, Issue 5, May 2025
DOI: 10.17148/IJIREEICE.2025.13509

D). Proposed Workflow:

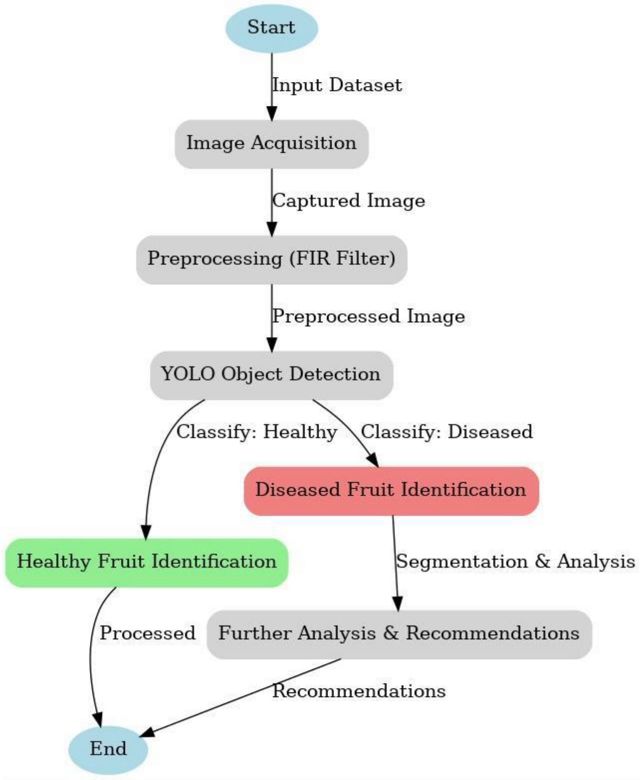

Fig 2. Flow Chart

Fig. 2 Represents a flowchart of the fruit classification and disease detection process. The system starts with dataset input and image acquisition. The captured images undergo preprocessing using a FIR filter to remove noise. Pre-processed images are then analysed using YOLO object detection to classify the fruit as either healthy or diseased**.**
If the fruit is healthy, it is directly marked as processed. If identified as diseased, the system performs segmentation and analysis to identify the type and severity of the disease. This is followed by further analysis and the generation of recommendations for treatment or handling. The process concludes after classification and recommendation**.**

IV. RESULTS

Fig.3

Fig.4

DOI: 10.17148/IJIREEICE.2025.13509

The first image (**Fig.3**) features a **clean, healthy banana.** The system identifies it as **"un-diseased"** with **57% confidence, operating at 3.48 FPS**

The second image **(Fig.4)** shows a mobile screen displaying bananas with visible signs of disease. The system detects this with a **52%** confidence level and labels it as **"diseased". The frame rate is 2.89 FPS.**
These results indicate the model's capability to differentiate between diseased and healthy fruits with moderate confidence in real-time scenarios**.**

V. MODEL TEST PERFORMANCE

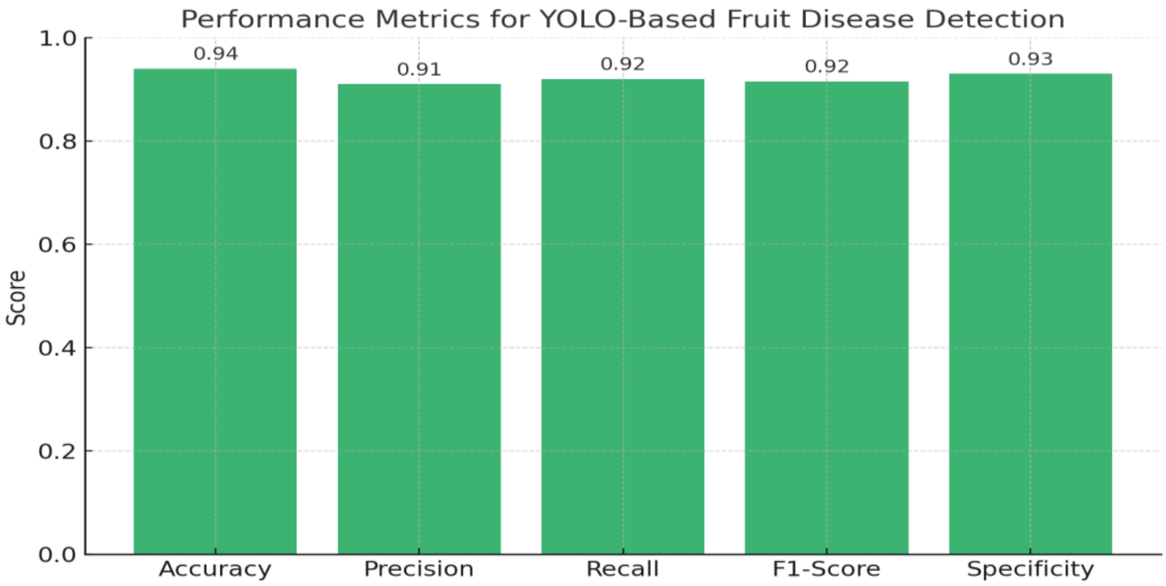

Fig.5
Performance chart image for the YOLO-Based Fruit Disease Detection

Fig.5 Shows the performance metrics of a YOLO-based fruit disease detection model. The metrics indicate high effectiveness:

Accuracy: 0.94
Precision: 0.91
Recall: 0.92
F1-Score: 0.92
Specificity: 0.93

These values suggest that the model performs very well across all key evaluation metrics, indicating strong overall reliability in detecting fruit diseases**.**

VI. CONCLUSION & FUTURE SCOPE

Conclusion:
The YOLO-based real-time fruit disease detection system presented in the report demonstrates high performance, with metrics such as accuracy (0.94), precision (0.91), recall (0.92), F1-score (0.92), and specificity (0.93). These results validate the system's effectiveness in accurately identifying both healthy and diseased fruits under varying conditions. By integrating YOLO's powerful object detection capabilities with enhanced image preprocessing using FIR filters, the system achieves superior detection performance without compromising image quality or resolution. This approach addresses key limitations of traditional methods, such as inefficiency, inaccuracy, and lack of scalability.

Overall, the system provides a fast, reliable, and scalable solution for real-time agricultural monitoring, which can help reduce postharvest losses and improve productivity in precision farming.

Future Scope:

1. Integration with Drones and IoT Devices:
Automating large-scale monitoring of orchards and farms using drones equipped with the system.
Real-time alerts and disease analytics through IoT connectivity.

2. Expansion to Multiple Crops and Diseases:
Extend the dataset and training to include a wider range of fruit types and disease classes.
Fine-tune models for crop-specific conditions.

3. Advanced Deep Learning Enhancements:
Incorporate attention mechanisms (e.g., CBAM, SE blocks) to further improve detection in complex backgrounds or occluded images.
Explore lightweight versions like YOLO-NAS or YOLOv8n for edge devices.

4. Mobile and Web Application Deployment:
User-friendly applications for farmers to upload images and receive instant diagnostic feedback.

5. Integration with Agricultural Decision Support Systems (DSS):
Use detected data to recommend treatment plans, pesticide use, or harvesting schedules.

6. Cloud-Based Data Aggregation and Analysis:
Long-term data collection for trend analysis, disease outbreak prediction, and yield optimization.
This future development can significantly enhance the role of AI in smart agriculture, contributing to sustainable and technology-driven farming.

VII. ACKNOWLEDGEMENT

We would like to express our sincere gratitude to all those who supported and guided us throughout the successful completion of our project, "**YOLO-Based Real-Time Fruit Disease Detection System**."

First and foremost, we are profoundly grateful to our project guide, **Mrs NOOR AYESHA**, for their invaluable guidance, consistent support, and expert advice during every phase of the project. Their insights greatly enhanced the quality of our work.

We extend our heartfelt thanks to the **Department of Electronics and Communication Engineering, PES College of Engineering, Mandya**, for providing the infrastructure and resources necessary to carry out this research effectively.
We are also thankful to our **Head of the Department**, faculty members, and lab staff for their encouragement and technical assistance whenever required.

This project has been a great learning experience, and we are deeply appreciative of everyone who contributed to its success.

REFERENCES

[1]. Chiu, M. T., et al. (2020). Agriculture-Vision: A Large Aerial Image Database for Agricultural Pattern Analysis. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), pp. 2825–2835.
[2]. Xu, N. (2021). Image Processing Technology in Agriculture. Journal of Physics: Conference Series, 1881(3), 032097.
[3]. Liu, C., et al. (2018). Object Detection Based on YOLO Network. 2018 IEEE 4th Information Technology and Mechatronics Engineering Conference (ITOEC).
[4]. Santoso, A. D., et al. (2024). Development of PCB Defect Detection System Using Image Processing with YOLO CNN Method. International Journal of Artificial Intelligence Research, 6(1.1).
[5]. Zhao, J., et al. (2024). YOLO-Granada: A Lightweight attentions YOLO for Pomegranate Fruit Detection. Scientific Reports, 14(1), 16848.
[6]. de Moraes, J. L., et al. (2023). YOLO-Papaya: A Papaya Fruit Disease Detector and Classifier Using CNNs and Convolutional Block Attention Modules. Electronics, 12(10), 2202.