Fruit Classification and Detection Using Deep Learning and Yolo Model with Full Stack Web Development

[1] Mrs.muddana Sarada, [2] SRIRAM V V V N S M PRANEETA, [3] TADI DIMPLE LAKSHMI PRIYA, [4] TALLURI HARSHITHA

[1]Assistance professor, Dept CSE-AI&ML, St.Ann's College of Engineering and Technology, Nayunipalli (V), Vetapalem (M), Chirala, Bapatla Dist, Andhra Pradesh – 523187, India

[2,3,4]U. G Student, Dept CSE-AI&ML, St.Ann's College of Engineering and Technology, Nayunipalli (V), Vetapalem (M), Chirala, Bapatla Dist, Andhra Pradesh – 523187, India.

ABSTRACT

Fruit classification and detection play a crucial role in smart agriculture, retail automation, and food quality monitoring systems. This work presents an intelligent fruit recognition system using the YOLO deep learning model integrated with a full-stack web application for real-time deployment. The system captures fruit images through camera or uploaded input and processes them with a trained YOLO model to classify type, detect quality, and estimate ripeness level. The proposed framework supports multiple fruit categories with high accuracy, fast inference speed, and robust detection in challenging lighting backgrounds. The full-stack platform provides seamless interaction using a responsive front-end, REST APIs, and cloud-based backend to manage model execution. The system helps farmers, vendors, and industries automatesorting, reduce manual error, and improve efficiency. Real-time visualization enables instant results with bounding boxes and classification labels. The project demonstrates a scalable AI-powered fruit monitoring architecture suitable for real-world agricultural applications.

INTRODUCTION

The advancement of artificial intelligence and deep learning has significantly transformed automation processes in agriculture and food industries. Fruit detection and classification are essential tasks for grading, pricing, and quality monitoring, yet manual inspection is slow, inconsistent, and prone to human error. Recent progress in convolutional neural networks and object detection models like YOLO has made real-time fruit identification more efficient and accurate. Integrating such intelligent models into a full-stack web application enhances accessibility and usability for non-technical users. This system allows fruits to be detected from images or live camera feeds and classified instantly on a browser platform. The web interface enables interactive visualization of predictions, making the system practical for markets, warehouses, and farms. Moreover, the proposed framework supports scalability, portability, and real-world deployment feasibility. This project aims to bridge AI technology with web solutions for smart fruit recognition systems.

LITERATURE SURVEY

Several researchers have explored computer vision methods for fruit recognition using image processing and machine learning. Earlier approaches relied on handcrafted features such as color histograms, texture patterns, and shape descriptors, which struggled with accuracy under varying lighting and background noise. With the evolution of deep learning, CNN-based models significantly improved classification performance in agricultural datasets. Studies indicate that YOLO architectures outperform traditional methods in speed and precision for multi-object fruit detection tasks. Research also highlights the importance of dataset size, augmentation, and domain-specific training for achieving high reliability. Existing systems mostly focus on offline analysis without providing real-time accessible platforms. Many studies fail to integrate web-based automation, limiting practical usability. Thus, literature suggests a strong need for a robust, real-time, web-deployable fruit detection solution.

RELATED WORK

Previous researchers have implemented fruit recognition using CNN, Faster R-CNN, SSD, and YOLO frameworks to enhance detection accuracy. Some studies developed mobile applications for fruit detection, but they often lacked server-based analytics and large-scale processing. Research works show that YOLOv5 and YOLOv8 models are widely adopted for agricultural object detection due to their speed-accuracy balance. Certain projects integrated IoT devices for farm monitoring but did not include intelligent web platforms for classification. A few works applied machine learning for ripeness estimation, yet lacked robust datasets and real-time processing capability. Most studies demonstrate feasibility in experimental setups rather than real-world operational platforms. Compared to these works, the proposed system integrates detection, classification, cloud storage, and web visualization in one framework. Thus, it extends beyond research prototypes toward deployable smart agriculture technology.

EXISTING SYSTEM

The existing fruit detection processes in markets and farms are mostly manual, relying on human inspection for sorting and grading. Manual examination is time-consuming, labor-intensive, and highly subjective, leading to inconsistent quality evaluation. Some semi-automated systems exist, but they primarily use simple image processing, which struggles in complex backgrounds and varied lighting. Traditional classification models often fail when fruits overlap or appear partially visible. Most existing digital systems lack real-time capability and cannot process large volumes of images instantly. Additionally, many solutions do not support web deployment, making access limited to specific devices. Cost and maintenance constraints also restrict advanced technology adoption in agriculture. Therefore, current systems are insufficient to meet modern smart farming automation needs.

PROPOSED SYSTEM

The proposed system introduces a deep learning-powered fruit classification and detection platform using the YOLO model integrated into a full-stack web application. The system captures fruit images through live camera feed or uploads and processes them with YOLO to detect fruit type and bounding location with high speed and accuracy. A trained dataset enables recognition of multiple fruit categories and ripeness levels. The backend server handles image processing and model prediction, while the frontend visualizes results interactively with labeled bounding boxes. Cloud or local database storage supports logging detected results for further analysis. The platform ensures user-friendly access using a responsive and secure web interface. Real-time analytics and visualization make the system suitable for shops, farms, warehouses, and quality inspection centers. This proposed framework enhances automation, reduces labor, and improves efficiency in fruit management.

SYSTEM ARCHITECTURE

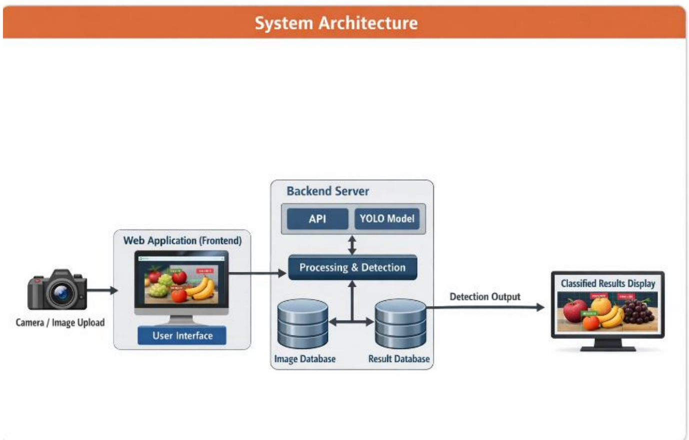

Fig 1:Fruit classification detection system

METHODOLOGY DESCRIPTION

The system begins by collecting fruit images from datasets and real-time camera sources for training and testing. The dataset undergoes preprocessing including resizing, normalization, and augmentation to enhance robustness. The YOLO model is trained to detect fruit objects by learning spatial features and bounding box annotations. During deployment, input images are sent from the web interface to the backend API, where the trained YOLO model performs inference. The detected fruits are classified and returned with bounding boxes and confidence scores. The frontend displays detection results dynamically to users in real-time. The backend is implemented using frameworks like Flask or Node.js with Python model integration. The full-stack setup ensures seamless communication, real-time processing, and efficient result visualization.

RESULTS AND DISCUSSION

Fig 2: Real time detection results

CONCLUSION

This project demonstrates an efficient fruit classification and detection system using YOLO deep learning integrated into a full-stack web platform. The system provides real-time detection capabilities with high accuracy and fast processing speed, addressing major limitations of manual fruit inspection. The web-based deployment ensures accessibility, scalability, and practical usability across agricultural and commercial environments. The framework enhances automation in fruit sorting, grading, and monitoring processes. Results prove that YOLO is highly suitable for agricultural object detection tasks. The project bridges AI technology with practical deployment through modern web development. It provides a strong foundation for future advancements in smart agriculture applications. Overall, the system is reliable, efficient, and ready for real-time operational use.

FUTURE SCOPE

The system can be extended to detect fruit quality parameters such as ripeness percentage, disease detection, and spoilage level. Integration with IoT devices can enable automated sorting machines in farms and warehouses. Mobile app deployment can provide portability for farmers and vendors. Cloud-based AI services may allow large-scale processing and analytics. More fruit types and larger datasets can be included to improve robustness. Real-time pricing prediction and yield estimation can also be integrated. AI-powered decision support tools can help farmers make better crop management decisions. Thus, the system has vast potential for future smart agriculture innovations.

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