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Banana Ripeness Detection and Smart Environmental Monitoring System Using YOLOv8, Random Forest, and IOT Sensors

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Abstract - This paper presents the design and implementation of a Banana Ripeness Detection and Smart Environmental Monitoring System that integrates deep learning, machine learning, and Internet of Things (IoT) technologies to provide an automated, non-destructive, and real-time solution for fruit quality assessment and environmental condition management. The proposed system comprises two integrated modules. The first module employs a YOLOv8 deep learning model trained on a Roboflow-prepared dataset to classify banana images into five categories: Unripe, Semi-ripe, Ripe, Overripe, and Disease Detected. Upon detection of a critical ripeness stage or disease, the system automatically dispatches an email notification via SMTP. The second module performs continuous environmental monitoring using four IoT sensors (MQ135, DHT11, soil moisture, and pH sensor), analysed by a Random Forest classifier to determine Normal or Abnormal conditions. In abnormal cases, SMS alerts are sent via a GSM module and an irrigation pump is activated automatically. The YOLOv8 model achieved a mean Average Precision (mAP@0.5) of 89.6% and the Random Forest classifier achieved 96.8% overall accuracy. The system provides a scalable, cost-effective, and practical framework for precision agriculture.

Key Words: YOLOv8, Random Forest, IoT Sensors, Banana Ripeness Detection, Precision Agriculture, Smart Environmental Monitoring, Deep Learning, Object Detection.

1. INTRODUCTION

Bananas are among the most widely consumed fruits globally and constitute a critical component of agricultural economies in tropical and subtropical regions. Bananas are highly perishable, and their ripeness changes rapidly under varying environmental conditions including temperature, humidity, and gas concentration. Accurately determining ripeness at different stages of the supply chain is essential for minimising post-harvest losses, maintaining fruit quality, and maximising commercial value.

Current methods of ripeness assessment are predominantly manual, relying on visual judgement of peel colour. This approach is inherently subjective, inconsistent, and impractical at scale. Laboratory-based biochemical testing provides objective data but is destructive, time-consuming, and unsuitable for real-time monitoring. This project proposes an automated, non-destructive, real-time system that simultaneously assesses banana ripeness from visual data and monitors surrounding environmental conditions, providing timely alerts and initiating corrective actions without human intervention.

2. LITERATURE SURVEY

Traditional banana quality assessment relies on manual visual inspection, which is subjective and unscalable. Image processing methods using SVM and KNN classifiers improved objectivity but require manual feature engineering and perform poorly under variable real-world conditions. CNN-based models achieved higher accuracy but lack object detection and localisation capability. Destructive laboratory testing using starch content and total soluble solids measurement is accurate but commercially impractical. IoT-based environmental monitoring has been explored for post-harvest management but rarely integrated with visual detection. Recent work combining YOLO-family detectors with IoT sensor networks demonstrates the feasibility of comprehensive, unified agricultural monitoring systems.

3. . RESULTS

Performance Comparison of YOLOv8 Ripeness Detection and Environmental Monitoring:

Table 1: YOLOv8 Classification Performance Metrics

Class	Precision	Recall	F1-Score	mAP@0.5
Unripe	0.94	0.92	0.93	0.91
Semi-ripe	0.91	0.89	0.90	0.88
Ripe	0.96	0.95	0.95	0.94
Overripe	0.93	0.91	0.92	0.90
Disease	0.88	0.86	0.87	0.85
Mean	**0.924**	**0.906**	**0.914**	**0.896**

Table 2: Random Forest Environmental Classification Results

Class	Precision	Recall	F1-Score	Support
Normal (0)	0.97	0.98	0.975	512
Abnormal (1)	0.96	0.95	0.955	488
Overall Accuracy	-	-	**96.8%**	**1000**

Table 3: System Response Summary

Trigger Condition	Response Action	Response Time	Status
YOLOv8 detects ripeness	Email via SMTP	3-8 sec	Success
Disease / Overripe	Priority email + image	3-10 sec	Success
Random Forest: Abnormal	SMS via GSM module	5-12 sec	Success
Soil moisture low	Irrigation pump ON	< 1 sec	Success

4. EXISTING METHODOLOGY

Existing banana ripeness assessment methods are summarised in three primary categories. Manual visual inspection uses peel colour progression from green to yellow to brown as the ripeness indicator. Machine learning-based image classification applies SVM, KNN, or standard CNN architectures to extract features from banana images and assign ripeness labels. Destructive laboratory testing measures internal biochemical parameters including starch content, total soluble solids, and titratable acidity.

Limitations: manual inspection is subjective and inconsistent; SVM and KNN methods underperform in uncontrolled environments; CNN classifiers lack localisation capability; none of the existing approaches integrate visual assessment with environmental monitoring; destructive testing renders fruit commercially unviable.

5. PROPOSED METHODOLOGY

The proposed system is designed as a dual-module integrated platform combining computer vision-based fruit ripeness assessment with IoT sensor-based environmental monitoring. Both modules operate in parallel and are logically connected through a unified alert and response framework.

5.1 Module 1 - Banana Ripeness Detection Using YOLOv8

Module 1 employs the YOLOv8 (You Only Look Once, version 8) object detection architecture developed by Ultralytics. YOLOv8 is a single-stage, anchor-free model that processes the entire image in a single forward pass, enabling fast inference suitable for real-time detection. The training dataset is prepared using Roboflow with dataset augmentation including random flipping, brightness adjustment, rotation, and mosaic augmentation. The dataset is split 70/20/10 for training, validation, and testing respectively. The model classifies detected bananas into five categories: Unripe, Semi-ripe, Ripe, Overripe, and Disease Detected. Upon detection, the system dispatches email notifications via SMTP containing the class label, confidence score, and a timestamped image of the detection frame.

5.2 Module 2 - Environmental Monitoring Using IoT and Random Forest

Module 2 implements a real-time environmental monitoring subsystem using four IoT sensors: MQ135 gas sensor (air quality, 10-300 ppm), DHT11 temperature and humidity sensor (0-50°C, 20-90% RH), soil moisture sensor (0-100%), and pH sensor (0-14 pH). Sensor data is processed by a Random Forest ensemble classifier trained on approximately 5,000 labelled samples. The classifier determines whether environmental conditions are Normal or Abnormal. On abnormal detection, the system triggers an SMS alert via GSM module and activates an automated irrigation pump via relay control when soil moisture falls below a defined threshold

6. DISCUSSION

The proposed dual-module system achieves simultaneous improvements across all monitored parameters. The YOLOv8 model attains a mean F1-score of 0.914 across five ripeness classes, with the Ripe class achieving the highest performance (F1: 0.95, mAP@0.5: 0.94). The Disease Detected class shows the lowest performance (F1: 0.87), attributable to the higher intra-class visual variability of disease symptoms compared to ripeness-stage colour progression. The Random Forest classifier demonstrates robust discrimination between Normal and Abnormal environmental conditions with 96.8% overall accuracy. The automated response framework functions within acceptable real-time latencies — email alerts within 3-8 seconds of detection and SMS alerts within 5-12 seconds of an abnormal environmental event. The automated irrigation relay activates within 1 second of threshold breach, confirming suitability for responsive agricultural control.

7. CONCLUSION

A Banana Ripeness Detection and Smart Environmental Monitoring System has been designed, implemented, and evaluated using YOLOv8 deep learning, Random Forest machine learning, and IoT sensor integration on a Raspberry Pi platform. The YOLOv8-based ripeness detection module achieved a mAP@0.5 of 89.6% across five banana classification categories. The Random Forest environmental monitoring module achieved 96.8% overall classification accuracy. The dual-channel alert system (SMTP email and GSM SMS) and the automated irrigation control were verified to function reliably in all tested scenarios. The system offers a non-destructive, real-time, scalable, and cost-effective solution suitable for deployment in banana farming, cold chain storage, and supply chain management.

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