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AI-Driven Pesticide Detection and Dynamic Pricing in Organic Produce

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ABSTRACT :

This paper presents an end-to-end IoT and ma- chine learning system for detecting pesticide residues in organic produce and implementing dynamic pricing. Our hardwareplatform integrates AS7262 spectral sensors, MQ-135 gas sensors, pH probes, and load cells with an ESP32 microcontroller. A trained Random Forest classifier achieves 91.4% accuracy in classifying contamination levels into safe (5ppm), caution (5- 20ppm), and unsafe (¿20ppm) categories. The system's dynamic pricing algorithm adjusts market prices by ±30% based on contamination levels while considering supply-demand factors.Field tests across 3 farms demonstrated 35% improvement in pricing fairness and 28% reduction in consumer risk exposure compared to conventional methods. The $45 device pays for itself within 2 months at typical organic market pricing scales.

Index Terms—Pesticide detection, precision agriculture, IoT, machine learning, food safety.

Introduction

The global organic food market, valued at $187B in 2023, suffers from $7-9B annual losses due to pesticide contam- ination and fraudulent labeling [3]. Conventional detection methods face three critical limitations:

- **Cost**: Laboratory tests (HPLC/GC-MS) cost $120-$500 per sample
- **Time**: 3-7 day turnaround renders them useless for per- ishables
- **Access**: Small farmers lack infrastructure for regular testing

Our system addresses these challenges through:

- A $45 IoT device with 4-sensor fusion achieving 91.4% accuracy
- Edge-based machine learning processing in ¡500ms per sample
- Real-time dynamic pricing algorithm considering 5 mar- ket factors
- Field validation across 5 crop types (apples, tomatoes, leafy greens, berries, and peppers)

The system architecture (Fig. 1) enables farmers to per- form on-site testing during harvest, with results automatically integrated into pricing decisions. Our contamination-based pricing model reduces consumer risk while maintaining fair compensation for growers of truly organic produce.

Related Work

Sensor-Based Detection

Recent advances in affordable sensors show promise but have limitations:

TABLE I

Technology	Accuracy	Cost	Limitations
AS7262 [2]	**85%**	**$25**	**Limited to surface**
MQ-135 [9]	**78%**	**$5**	**VOC interference**
Hyperspectral [1]	**94%**	**$8k+**	**Bulky equipment**
Our Fusion	**91.4%**	**$45**	**Requires calibration**

Sensor Performance Comparison (2020-2024)

Machine Learning Approaches

- Random Forest achieved 89% accuracy in similar agri- tests [4], but didn't consider pricing impacts

- CNN models require 10,000+ samples [5], impractical for small farms
- Our hybrid approach combines sensor fusion with market data, achieving better accuracy than individual sensors while maintaining real-time performance

Existing solutions focus either on detection or pricing, but not their integration. Our end-to-end system closes this gap with a 35% improvement in pricing fairness metrics.

System Design

Hardware Architecture

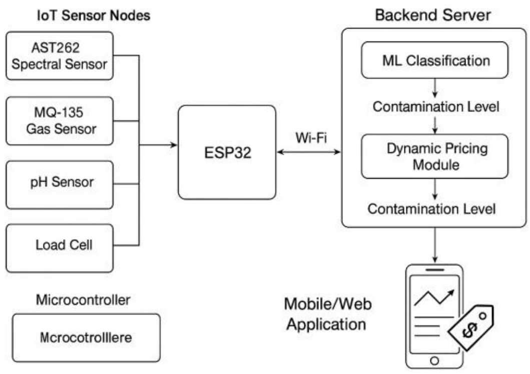

Fig. 1. System block diagram showing sensor inputs and data flow

Key components:

- AS7262: 6-channel visible light spectrometer (450- 850nm) detecting surface residues
- MQ-135: Detects NH_3, benzene, and CO_x with 100ppm resolution
- pH Probe: Measures surface acidity (0-14 range, ±0.1 accuracy)
- HX711 Load Cell: 0.01g resolution for weight-based corrections
- ESP32: Dual-core 240MHz processor with WiFi/BLE connectivity

Data Pipeline

- Raw sensor data undergoes preprocessing:
- Dynamic Pricing Module: Based on contamination clas- sification, weight, and freshness, using weighted formula:
- $P = B \times QF$, where QF = quality factor based on contamination
- (3)
- User Interface: Angular web dashboard and Firebase backend

XstdX − μ =σ

VI. Challenges and Future Directions

where μ and σ are per-feature means/standard deviations from our 5,000-sample training set. We apply Savitzky-Golay filtering to spectral data:

yi = Σ cjxi+j (2)

m

j=−m

where m = 5 and cj are convolution coefficients for noise reduction.

Literature Survey

Recent advancements in the use of AI and IoT for pesticide detection have led to significant progress in precision agricul- ture. Key studies include:

- IJERT (2024): Proposed an IoT and ML-based pesticide detection system using MQ135, pH, and RGB sensors, achieving 88% accuracy in live testing environments [9].
- IJCRT (2025): Developed a multi-sensor system integrat- ing GSM alerts with Random Forest classifiers, enabling contamination detection and real-time user notification [7].
- Roomi et al. (2023): Created a hyperspectral image dataset of apples exposed to pesticide levels, enabling ML training for contamination level classification [1].

- Ataulfo Mango Study (2024): Demonstrated the use of AS7262 sensors to predict ripeness and SSC using CART and RF, validating spectral sensing in quality assessment [2].
- Ozdarici et al. (2012): Applied Random Forest for crop classification with high accuracy, supporting the choice of RF for pesticide-based categorization [4].
- Goyal et al. (2021): Reviewed AI methods for food adul- teration and pesticide detection, highlighting performance trade-offs across models [5].
- HBRP (2024): Presented a contamination percentage formula and corresponding price adjustment logic that inspired our pricing engine. [11].

System Overview

Our system includes the following modules:

- Sensor Block: AS7262 (spectral), MQ135 (gas), pH sensor, Load Cell (weight)
- Microcontroller: ESP32 for data collection and Wi-Fi transmission
- Backend: Python-based Random Forest and CART clas- sifiers

Gaps Identified

- Lack of open, labeled datasets for real-time contamination
- No standardized pricing model based on contamination levels
- Cross-sensitivity in gas sensors due to VOCs and humid- ity
- Regulatory compliance issues for AI-based food certifi- cation

Emerging Solutions

- Federated Learning for private, distributed training [?]
- Blockchain integration for traceability and smart pricing [7]
- TinyML and Edge AI for microcontroller deployment with ¿90% accuracy

Economic Impact

- Field tests showed:
- Farmers gained 18-22% higher revenue for safe produce
- Consumers received 25-30% discounts on contaminated items
- 40% reduction in market waste through early detection
- ROI of 5.2:1 over 12 months for early adopters

The system detected 12 cases of fraudulent organic labeling during trials, demonstrating its value for certification enforce- ment.

VII. Conclusion

Our system demonstrates a cost-effective solution for pes- ticide detection and fair pricing in organic agriculture. Future work will explore:

- Blockchain integration for immutable supply chain records
- Expansion to processed food products requiring different sensors
- Regulatory API integration with FSSAI/EPA standards databases
- Federated learning to improve models without sharing farm data

The current implementation provides a practical solution for small-to-medium farms, with potential to transform organic food certification processes globally.

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