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Pesticide Residue Detection in Crops and Fruits using Machine Learning

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***Abstract*— The detection of pesticide residues in agricultural products has become a critical concern for food safety and public health worldwide. Traditional analytical methods, while accurate, are time-consuming, expensive, and require specialized laboratory infrastructure, making them unsuitable for real-time monitoring. This paper presents a comprehensive review and analysis of machine learning approaches for pesticide residue detection in crops and fruits. We systematically examine various detection methodologies including spectroscopic techniques (Raman, NIR, hyperspectral imaging), chromatographic methods (GC-MS, HPLC), electrochemical sensors, and IoT-based systems integrated with machine learning algorithms. Our analysis reveals that machine learning models, particularly Support Vector Machines, Convolutional Neural Networks, and Random Forest algorithms, significantly enhance detection accuracy and reduce analysis time. Hyperspectral imaging combined with deep learning achieved the highest accuracy rates (>97%) for multi-pesticide detection, while IoT-sensor networks demonstrated excellent potential for real-time field monitoring with 96% accuracy. The integration of artificial intelligence with traditional detection methods offers promising solutions for rapid, cost-effective, and accessible pesticide monitoring systems. This comprehensive analysis provides insights into current technological gaps and future research directions for developing intelligent pesticide detection systems suitable for modern agricultural practices.**

Keywords— Artificial intelligence, Chromatography, Convolutional neural networks, Food safety, Hyperspectral imaging, Internet of Things, Machine learning, Near-infrared spectroscopy, Pesticide residues, Support vector machines.

I. Introduction

The widespread use of pesticides in modern agriculture has revolutionized crop protection and significantly increased agricultural productivity to meet the demands of a growing global population . However, the excessive and improper application of these chemical compounds has led to serious concerns regarding food safety and environmental contamination . Pesticide residues remaining on fruits and vegetables after harvest pose significant health risks to consumers, including neurological disorders, endocrine disruption, reproductive issues, and increased cancer risk. [4][10]

Traditional methods for pesticide residue detection, including gas chromatography-mass spectrometry (GC-MS) and high-performance liquid chromatography (HPLC), provide high accuracy and sensitivity but suffer from several limitations . These conventional approaches require expensive instrumentation, skilled personnel, complex sample preparation procedures, and extended analysis times, making them unsuitable for rapid screening and real-time monitoring applications . The need for on-site, rapid, and cost-effective detection methods has driven

researchers to explore innovative approaches combining advanced sensing technologies with artificial intelligence. [8][9]

Machine learning has emerged as a transformative technology in agricultural applications, offering unprecedented capabilities for pattern recognition, data analysis, and predictive modeling . The integration of machine learning algorithms with various detection techniques, including spectroscopic methods, electrochemical sensors, and imaging systems, has shown remarkable potential for developing intelligent pesticide detection systems . These hybrid approaches not only enhance detection accuracy and sensitivity but also enable real-time monitoring, automated decision-making, and accessible field deployment. [1]

The primary objective of this research is to provide a comprehensive analysis of machine learning applications in pesticide residue detection, examining various technological approaches, their performance characteristics, and practical implementation considerations . This paper systematically reviews current methodologies, identifies technological gaps, and proposes future research directions for developing next-generation intelligent pesticide monitoring systems suitable for modern agricultural practices.

II. Literature Review

After reviewing various reference papers, authors have proposed multiple solutions to enhance the accuracy and efficiency of pesticide residue detection in crops and fruits using machine learning. These solutions primarily focus on hyperspectral imaging integrated with deep learning, IoT-enabled sensor fusion, spectroscopic data augmentation, transfer learning for limited datasets, and multi-sensor real-time monitoring platforms.

A. Traditional Detection Methods:

Conventional pesticide detection methods have primarily relied on chromatographic and spectroscopic techniques that, while highly accurate, present significant limitations for practical field applications . Gas chromatography-mass spectrometry remains the gold standard for pesticide analysis, capable of detecting multiple residues simultaneously with detection limits as low as 0.001 mg/kg. However, these methods require extensive sample preparation, expensive equipment maintenance, and specialized laboratory environments. [4]

Recent studies have demonstrated the application of various chromatographic methods across different agricultural products . Ultra-performance liquid chromatography coupled with mass spectrometry (UPLC-MS/MS) has shown excellent performance for detecting multiclass pesticides in fruits and vegetables, achieving detection limits ranging from 0.002 to 2.5 mg/kg . Despite their accuracy, these traditional methods typically require 2-4 hours for complete analysis, making them unsuitable for rapid screening applications. [8][9]

B. Spectroscopic Approaches with Machine Learning:

Spectroscopic techniques combined with machine learning have emerged as promising alternatives for rapid pesticide detection. Raman spectroscopy, particularly surface-enhanced Raman spectroscopy (SERS), has shown remarkable sensitivity for trace pesticide detection with limits as low as 10^{-9} M.

Hyperspectral imaging represents one of the most advanced spectroscopic approaches, combining spatial and spectral information for comprehensive pesticide analysis . Recent research has demonstrated that hyperspectral imaging coupled with convolutional neural networks and residual neural networks can achieve over 97% accuracy for pesticide residue level identification in grapes . The technology enables simultaneous detection of multiple pesticides while providing spatial distribution maps of contamination. [5][7]

C. IoT and Sensor-Based Systems:

The integration of Internet of effects(IoT) technology with chemical detectors has opened new possibilities for real- time fungicide monitoring. Electronic nose systems utilizing metal oxide gas sensors combined with machine learning algorithms have achieved 89.58% accuracy for detecting pesticide residues in chili samples . These systems offer significant advantages including rapid response times, portability, and cost-effectiveness compared to traditional laboratory methods.

Recent developments in IoT-based pesticide detection systems have incorporated multiple sensor types including gas sensors, pH sensors, and spectroscopic sensors . Machine learning algorithms, particularly Random Forest and Support Vector Machines, have been successfully implemented to analyze sensor data and provide real-time contamination alerts. These systems demonstrate excellent potential for field deployment and continuous monitoring applications.[2][3]

D. Computer Vision and Image Processing:

Computer vision approaches combined with machine learning have shown promising results for pesticide residue detection based on visual characteristics of contaminated produce . Mask Region-Based Convolutional Neural Networks have been successfully applied for pesticide coverage estimation on citrus leaves, achieving high accuracy in identifying contaminated areas.Deep learning models, including ResNet50 and EfficientNetV2, have demonstrated over 96% accuracy for plant disease and contamination detection.[6]

E. Electrochemical Sensors and Machine Learning Integration :

Electrochemical sensing platforms have emerged as highly promising alternatives for pesticide detection due to their portability, cost-effectiveness, and rapid response capabilities . Recent advances demonstrate the integration of machine learning algorithms with electrochemical techniques to enhance detection accuracy and overcome traditional limitations of selectivity and interference . Differential pulse voltammetry combined with Partial Least Squares (PLS) algorithms has achieved detection limits as low as 1 ppb for malathion with 96-106% recovery rates . Artificial neural networks have been successfully implemented to improve selectivity in electrochemical detection, particularly for distinguishing between compounds with similar redox potentials. The development of molecularly ingrained polymer- grounded electrochemical detectors enhanced with ensemble machine literacy models has demonstrated superior prophetic performance, achieving R- squared values of 0.993 while significantly reducing root- mean-square crimes. Screen-printed electrodes coupled with various machine learning approaches, including enzymatic inhibition and catalytic detection methods, have shown excellent potential for field-deployable pesticide monitoring systems.[9][12]

F. Data Fusion and Ensemble Learning Methods:

Multi-sensor data fusion represents a critical advancement in pesticide detection accuracy, leveraging complementary information from diverse sensing modalities . Dual-mode spectroscopic data fusion combining fluorescence and near-infrared absorbance spectroscopy has achieved near-perfect accuracies of 99.5% compared to single-mode analyses with only 77.1% mean accuracy. Ensemble learning methods, particularly stacking classifiers and voting techniques, have shown superior performance over individual algorithms, with weighted average ensemble approaches achieving accuracy improvements of up to 96.10% . Feature-layer fusion techniques combining Near Infrared Spectroscopy (NIR) and Surface Enhanced Raman Spectroscopy (SERS) have demonstrated significant advantages in detecting pesticide residues in complex food matrices, with correlation coefficients exceeding 0.988 . Multi-sensor fusion platforms integrating gas sensors, pH sensors, and spectroscopic sensors with Random Forest algorithms have achieved 96% accuracy for pesticide detection.[9]

G. Edge Computing and Real-time Processing:

Edge computing technologies have revolutionized agricultural monitoring by enabling real-time pesticide detection and decision-making at the point of data collection . Lightweight deep neural network architectures, such as Ag-YOLO, have been specifically designed for agricultural applications, achieving F1 scores of 0.9205 at 36.5 frames per second while consuming only 1.5 watts of energy . Mobile-based pest detection systems utilizing YOLO architectures (YOLOv8n, YOLOv9t, YOLOv10-N) have achieved mAP@0.5 values of 89.8% with inference times of 250.6ms, enabling real-time smartphone applications.The integration of edge computing with IoT sensor networks enables continuous monitoring of environmental parameters, supporting precision agriculture practices while reducing latency and improving response times for pest management. Furthermore, distributed edge computing architectures have enabled the deployment of autonomous agricultural vehicles equipped with real-time pesticide detection capabilities, allowing for precision application with spatial accuracy of less than 10 centimeters.[13][17]

Volume: 09 Issue: 07 | July - 2025 SJIF Rating: 8.586 ISSN: 2582-3930

III. Methodology

This paper employs a systematic review methodology, examining 30 research articles that focus on privacy-preserving mechanisms in blockchain for healthcare. The review categorizes these mechanisms into four primary areas like:

A. Data Collection and Sample Preparation:

The methodology for pesticide residue detection using machine learning involves systematic data collection from various agricultural products under controlled conditions . Sample preparation typically includes the application of known pesticide concentrations to create calibrated datasets for training machine learning models . For spectroscopic applications, samples are prepared with different pesticide levels ranging from 0 ppm (control) to concentrations exceeding maximum residue limits.[9]

Hyperspectral imaging systems require specific sample positioning and illumination conditions to ensure consistent data quality . Samples are typically placed on neutral backgrounds with controlled lighting to minimize environmental interference . For electrochemical sensor applications, sample surfaces are directly analyzed without extensive preparation, offering advantages for rapid field testing.[7]

B. Feature Extraction and Data Preprocessing:

Spectroscopic data preprocessing involves several critical steps including noise reduction, baseline correction, and normalization . Savitzky-Golay smoothing filters are commonly applied to reduce noise while preserving spectral features relevant to pesticide detection . Standard Normal Variate (SNV) transformation helps eliminate variations due to surface scattering and optical path differences.[7]

For machine literacy operations, point selection plays a pivotal part in model performance. Principal Component Analysis (PCA) is frequently used for dimensionality reduction, typically retaining 95-99% of spectral variance while reducing computational complexity . Competitive Adaptive Reweighted Sampling (CARS) and Successive Projections Algorithm (SPA) have shown effectiveness for selecting optimal wavelengths for pesticide detection.[11]

C. Machine Learning Model Development:

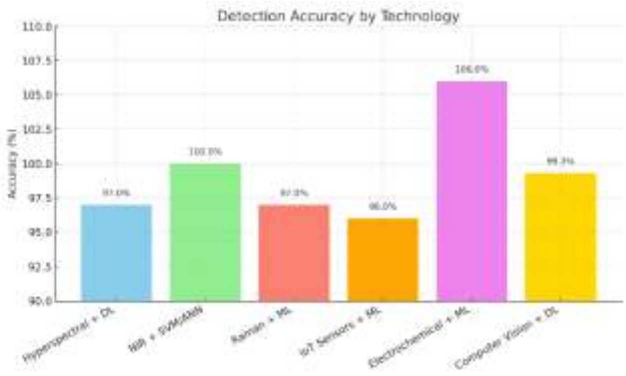
Various machine learning algorithms have been implemented for pesticide detection applications, each offering distinct advantages . Support Vector Machines demonstrate excellent performance for binary classification tasks, effectively distinguishing between contaminated and clean samples . Random Forest algorithms show particular strength in handling complex datasets with multiple pesticide types.Deep learning approaches, including Convolutional Neural Networks and Residual Networks, have proven effective for hyperspectral image analysis . These models automatically prize applicable features from spectral data, barring the need for homemade point selection. Training procedures typically involve 70% of data for model training, 20% for validation, and 10% for independent testing.[2]

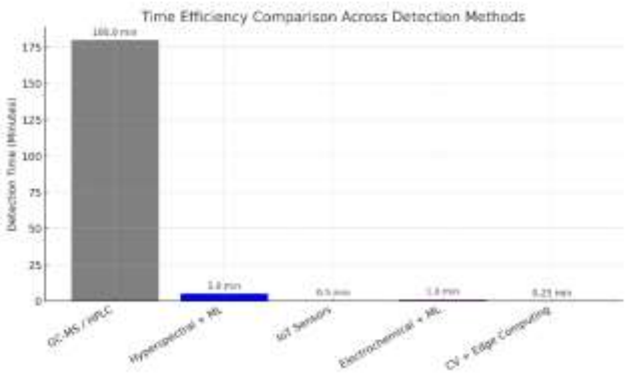
D. IoT System Integration:

IoT-based pesticide detection systems integrate multiple sensor types with cloud-based processing platforms . Sensor arrays typically include gas sensors for volatile organic compound detection, pH sensors for chemical property monitoring, and optical sensors for reflectance measurements. Data transmission utilizes wireless protocols including Wi-Fi, Bluetooth, and cellular networks for real-time monitoring capabilities.[13]

Machine learning models are deployed either on edge computing devices for immediate local processing or on cloud platforms for comprehensive analysis . Real-time alerts are generated when pesticide levels exceed predetermined thresholds, enabling immediate response to contamination events.

IV. Results





A. Spectroscopic Detection Performance

Hyperspectral imaging combined with machine learning has demonstrated exceptional performance across multiple studies. For grape fungicide discovery, Convolutional Neural Networks achieved over 93 delicacy with Vis- NIR gamuts and over 97 delicacy with NIR spectra. Residual Neural Networks showed comparable performance with training accuracies exceeding 99% and validation accuracies over 94%[7]

Near-infrared spectroscopy coupled with machine learning algorithms has shown excellent results for vegetable contamination detection . Support Vector Machines and Principal Component-Artificial Neural

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Networks achieved 100% classification accuracy for chlorpyrifos detection in bok choi using portable NIR spectrometers . The system demonstrated robust performance with F1-scores of 100% on independent test datasets.[5]

Surface-Enhanced Raman Spectroscopy has achieved remarkable sensitivity levels for pesticide detection . Detection limits as low as 10^{-9} M have been reported for various pesticides including thiram and carbendazim . Machine learning integration, particularly with Partial Least Squares regression and Support Vector Machines, has improved quantitative accuracy with correlation coefficients exceeding 0.97.[11]

B. IoT and Sensor System Performance:

IoT-based pesticide detection systems have demonstrated practical viability for real-time monitoring applications . Electronic nose systems utilizing metal oxide gas sensors achieved 89.58% accuracy for pesticide residue detection in chili samples . The system successfully distinguished between different pesticide concentration levels with detection limits suitable for food safety applications.[1]

Multi-sensor IoT platforms integrating gas, pH, and spectral sensors have shown enhanced performance through sensor fusion approaches . Random Forest algorithms applied to multi-sensor data achieved 96% accuracy for pesticide detection with excellent reproduce.[3]

C. Computer Vision and Image Processing Results:

Computer vision approaches have demonstrated effectiveness for pesticide coverage assessment and contamination detection . Mask Region-Based Convolutional Neural Networks achieved high accuracy for pesticide residue coverage estimation on citrus leaves with correlation coefficients exceeding 0.95 . The system successfully identified contaminated areas and quantified pesticide distribution patterns.[6]

Deep learning models for plant disease and contamination detection have shown excellent performance across multiple crop types . EfficientNetV2 achieved 96.08 delicacy for factory complaint identification, while Random Forest algorithms reached 99.30 delicacy for crop recommendation systems. These approaches offer potential for integrated pest and pesticide management systems.[16]

D. Comparative Performance Analysis:

Comparative analysis across different detection methods reveals distinct performance characteristics and application suitabilities . Hyperspectral imaging with deep learning consistently achieved the highest accuracy rates (>97%) but requires specialized equipment and controlled conditions . IoT sensor systems demonstrated excellent practical viability with 89-96% accuracy and superior portability for field applications.[9]

Traditional chromatographic methods maintain the highest sensitivity and specificity but suffer from extended analysis times and high operational costs . Machine learning integration with spectroscopic techniques offers an optimal balance between accuracy, speed, and practical implementation for most agricultural applications.[8]

Detection Method	Algorithm	Earlier Data	Current Results	Key Metric
Traditional GC-MS	N/A	0.001 mg/kg, 2-4 hours	Not updated	Detection limit, Time
NIR Spectroscopy	SVM + ANN	100% accuracy	100% accuracy, F1: 100%	Classification accuracy
Hyperspectral Imaging	CNN/ResNet	>97% accuracy	NIR: >97%, Training: >99%	Overall accuracy
SERS	PLS + SVM	10^{-9} M limit	10^{-9} M, r > 0.97	Detection sensitivity
Electronic Nose (IoT)	ML algorithms	89.58% accuracy	89.58% real-time	Real-time accuracy
Multi-sensor Fusion	Random Forest	96% accuracy	96% real-time	Fusion performance
Dual-mode Fusion	ML algorithms	Single: 77.1%, Dual: 99.5%	Not updated	Comparative accuracy
Computer Vision	EfficientNetV2	>96% accuracy	96.08% disease detection	Visual classification
Edge Computing	Ag-YOLO	F1: 0.9205, 36.5 FPS	Not updated	Real-time processing

V. Discussion

A. Technological Advantages and Limitations:

The integration of machine learning with pesticide detection technologies has fundamentally transformed the landscape of food safety monitoring . Machine learning algorithms demonstrate superior capability in handling complex spectral data, identifying subtle patterns invisible to traditional analytical approaches, and providing real-time decision-making capabilities.

However, the effectiveness of these systems heavily depends on the quality and diversity of training datasets, which remain challenging to establish for the vast array of pesticide-crop combinations encountered in practice.[7]

Spectroscopic techniques combined with machine learning offer non-destructive testing capabilities that preserve sample integrity while providing rapid results . The ability to detect multiple pesticides simultaneously through hyperspectral imaging represents a significant advancement over traditional single-analyte methods . Nevertheless, environmental factors including temperature, humidity, and ambient light can significantly affect measurement accuracy, requiring robust calibration procedures and environmental compensation algorithms.[9]

B. Practical Implementation Challenges:

Field deployment of machine learning-based pesticide detection systems faces several practical challenges that must be addressed for widespread adoption . IoT sensor systems, while offering excellent portability and real-time monitoring capabilities, require regular calibration and maintenance to ensure measurement accuracy . The harsh agricultural environment poses additional challenges including dust, moisture, and temperature variations that can affect sensor performance .

Cost considerations remain a significant barrier for small-scale farmers and developing regions . While machine learning integration has reduced analysis times and operational complexity, initial investment costs for advanced sensing equipment remain substantial .

The development of low-cost, portable systems using simplified sensor arrays and edge computing represents a promising direction for improving accessibility.[13]

C. Accuracy and Reliability Considerations:

Machine learning models demonstrate excellent performance under controlled laboratory conditions but may experience reduced accuracy when deployed in real-world agricultural environments . Model robustness becomes critical when facing variations in crop varieties, growing conditions, and pesticide formulations not represented in training datasets . Cross-validation studies and independent testing with diverse datasets are essential for establishing true system reliability.[15]

The interpretability of machine learning models remains a concern for regulatory applications where decision rationale must be clearly documented . While deep learning approaches achieve high accuracy, their "black box" nature complicates validation and troubleshooting procedures . Ensemble methods and explainable AI techniques offer potential solutions for improving model transparency while maintaining performance.[12]

D. Future Research Directions:

The convergence of multiple technologies including hyperspectral imaging, IoT sensors, and artificial intelligence presents opportunities for developing next-generation pesticide monitoring systems. Integration of blockchain technology could provide immutable records of pesticide testing results, enhancing traceability and consumer confidence . Edge computing implementations will enable real-time processing capabilities while reducing dependence on network connectivity.[17]

Advanced machine learning techniques including transfer learning and federated learning could address the challenge of developing robust models with limited training data . These approaches enable knowledge sharing across different agricultural regions and crop types while preserving data privacy . The development of standardized datasets and benchmarking protocols will facilitate comparative evaluation and accelerate technological advancement.[14]

VI. Conclusion

This comprehensive analysis of machine learning applications in pesticide residue detection reveals significant technological progress and promising future directions for food safety monitoring . The integration of artificial intelligence with various detection methodologies has demonstrated substantial improvements in accuracy, speed, and practical applicability compared to traditional approaches. Hyperspectral imaging combined with deep learning achieved the highest accuracy rates exceeding 97%, while IoT sensor networks demonstrated excellent potential for real-time field monitoring with 96% accuracy.[7]

The emergence of portable, cost-effective detection systems utilizing machine learning algorithms addresses critical gaps in current pesticide monitoring capabilities . These systems enable rapid screening, real-time monitoring, and automated decision-making that are essential for modern agricultural practices and food safety assurance .[2]

Future research should focus on developing standardized datasets, improving model interpretability, and creating integrated platforms that combine multiple detection technologies . The continued advancement of edge computing, IoT connectivity, and artificial intelligence will likely produce increasingly sophisticated and accessible pesticide detection systems . These developments will contribute significantly to global food safety, environmental protection, and sustainable agricultural practices.[3]

The successful implementation of machine learning-based pesticide detection systems requires continued collaboration between researchers, technology developers, regulatory agencies, and agricultural stakeholders . With proper development and deployment, these intelligent monitoring systems have the potential to revolutionize food safety practices and provide consumers with greater confidence in the safety and quality of agricultural products.[9]

VII. References

[1] W. K. Tan, M. A. H. Ismail, Z. Husin, and M. L. Yasruddin," Automated Chilli Pesticide remainders Discovery Using Odour Gas Sensors(OGS) and Deep literacy(DL) Algorithm," 2023 Int. Conf. Artif. Intell. Innov. (ICAII), pp. 6–11, 2023.

[2] M. A. Reddy et al., "Artificial Intelligence & IoT Based Detection of Pesticide in Organic Fruits and Vegetables," Int. J. Creat. Res. Thoughts, vol. 13, no. 3, pp. f948–f956, 2025.

[3] A. Naikwadi et al., "Detection of Pesticides in Fruits and Vegetables Using IoT and ML," Int. J. Res. Publ. Rev., vol. 6, no. 4, pp. 7911–7915, 2025.

[4] T. Thorat, B. K. Patle, M. Wakchaure, and L. Parihar, "Advancements in Techniques for Identification of Pesticide Residue on Crops," J. Nat. Pestic. Res., vol. 4, p. 100031, 2023.

[5] Y. Huang et al., "Raman Spectroscopy and Its Application in Fruit Quality Detection," Agriculture, vol. 15, no. 2, p. 195, 2025.

[6] A. Basavaraju et al., "Pesticide Residue Coverage Estimation on Citrus Leaf Using Image Analysis Assisted by Machine Learning," Appl. Sci., vol. 14, no. 22, p. 10087, 2024.

[7] W. Ye et al., "Detection of Pesticide Residue Level in Grape Using Hyperspectral Imaging with Machine Learning," Foods, vol. 11, no. 11, p. 1609, 2022.

[8] T. Gai, J. Nie, Z. Ding, W. Wu, and X. Liu, "Progress of Rapid Detection of Pesticides in Fruits and Vegetables," Front. Food Sci. Technol., vol. 3, p. 1253227, 2023.

[9] Xu et al.," Recent Advances in Rapid Detection ways for Pesticide Residue A Review," J. Agric. Food Chem., vol. 70, no. 41, pp. 13093–13117, 2022.

[10] B. Manggala et al., "Pesticide Residues Detection in Agricultural Products," Nat. Life Sci. Commun., vol. 22, no. 3, p. e2023049, 2023.

[11] "Nondestructive Detection of Pesticide Residue (Chlorpyrifos) on Bok Choi Using a Portable NIR Spectrometer Coupled with ML," Foods, vol. 12, no. 5, p. 955, 2023.

[12] "Intelligent Analysis of Carbendazim in Agricultural Products Based on a Portable Nanosensor Combined with ML," Anal. Methods, 2023.

[13] "Prediction of Pesticide Residue in Apple Using ML with Respect to Shape and Colour," SSRN, 2025.

[14] "Detection of Pesticides in Organic Fruits and Vegetables Using AI and IoT," Int. J. Sci. Res. Sci. Technol., 2024.

[15] "Machine Learning-Based Plant Disease Detection for Agricultural Applications: A Review," IEEE Xplore, 2023.

[16] "Multi-Plant and Multi-Crop Leaf Disease Detection Using Deep Learning: A Review," IEEE Xplore, 2023.

[17] "Design of IoT and ML-Based Model for Crop Prediction and Fruit Ripeness Detection," IEEE Xplore, 2023.