A CNN-Enabled Context-Aware Wireless Sensor Network for Smart Banana Cultivation

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Banana cultivation, a critical tropical crop, is highly sensitive to water stress, nutrient imbalance, and disease outbreaks, all exacerbated by climatic variability. Traditional wireless sensor network (WSN) systems rely on static thresholds, limiting their adaptability to dynamic field conditions. This study proposes a context-aware WSN framework integrated with a Convolutional Neural Network (CNN) for real-time field condition classification and intelligent decision support in banana farming. Multimodal data—including soil moisture, temperature, humidity, light intensity, and pH—are captured and normalized using z-score standardization. A 1D CNN architecture (three convolutional layers with ReLU activation, max pooling, and fully connected layers) processes the input feature vector X = [Ms, T, H, L, pH] to classify four agronomic contexts: Water Stress, Nutrient Deficiency, Disease Risk, and Normal Condition.

A dataset of 5,000 samples (3,200 real field records and 1,800 augmented via Gaussian noise and bootstrapping) was used for model training and validation with 5-fold cross-validation. The proposed CNN model achieved an accuracy of 95.3%, precision of 94.5%, recall of 95.2%, and F1-score of 94.8%, outperforming baseline SVM (83.1%) and Decision Tree (80.5%) models. Field deployment demonstrated a 28% improvement in water-use efficiency, a 41% reduction in disease incidence, and a 3.1% false alarm rate, confirming superior adaptability over rule-based systems. The framework provides scalable, real-time decision support, offering a transferable model for sustainable and intelligent precision agriculture.

Povzetek: Raziskava predstavlja pametni senzorski sistem s konvolucijsko nevronsko mrežo za banane, ki omogoča prilagodljivo in natančno odločanje v realnem času ter izboljša rabo vode in zdravje pridelka.

1 Introduction

Precision agriculture represents a transformative approach to modern farming, leveraging wireless sensor networks (WSNs), Internet of Things (IoT) technologies, and artificial intelligence (AI) to enable data-driven, site-specific crop management. By facilitating continuous monitoring of environmental and soil parameters, these systems optimize resource use, reduce operational costs, and enhance sustainability — key priorities in the context of climate change and growing food demand. Among tropical crops, banana (Musa spp.) holds exceptional economic and nutritional importance, serving as both a staple food and a major export commodity across developing regions. However, banana cultivation faces distinct agronomic challenges that differentiate it from other crops such as rice, grapes, or tomatoes. These include:

- High disease susceptibility, particularly to fungal infections such as Panama disease and black Sigatoka, which thrive under humid conditions.
- Soil heterogeneity and pH sensitivity, affecting nutrient uptake and plant health.
- Water management complexity, as bananas are sensitive to both drought and waterlogging.
- Microclimatic variability, which influences plant physiology and increases unpredictability in field conditions.

Conventional WSN-based systems in agriculture typically rely on rule-based decision-making with static thresholds for parameters like soil moisture or temperature. While effective for simple environments, these systems lack adaptability in dynamic field conditions, often leading to false alerts and inefficient interventions. In contrast, machine learning (ML) and deep learning (DL) models—particularly Convolutional Neural Networks (CNNs)—offer the ability to extract complex patterns and classify contextual states from multi-sensor data, enabling more robust, adaptive decision support. Despite promising results in other crops, existing studies often focus narrowly on disease detection using image data, without integrating environmental sensor fusion or context-aware decision-making. Moreover, few frameworks address real-time field condition classification tailored to banana's unique agronomic profile.

To address these gaps, this paper proposes a CNN-enabled context-aware WSN framework designed specifically for smart banana cultivation. The proposed system:

- Integrates heterogeneous sensor data (soil moisture, temperature, humidity, light, and pH) to capture real-time field conditions.
- Employs a CNN-based classifier to interpret environmental contexts into actionable categories: Water Stress, Nutrient Deficiency, Disease Risk, and Normal Condition.
- Provides real-time alerts and adaptive recommendations for irrigation, fertilization, and disease management.

Field experiments demonstrate the system's capacity to achieve 95.3% classification accuracy, 28% improvement in water-use efficiency, and 41% reduction in disease incidence compared to traditional rule-based methods. Beyond addressing crop-specific challenges, the framework establishes a scalable and transferable model for AI-driven precision agriculture, promoting resilience and sustainability across similar high-value crops. Figure 1 used to show how diseases and pests on banana plants affects [8]. By adopting a context-based approach, tailored to the specific requirements of banana plants, WSNs offer the potential to revolutionize banana cultivation practices and improve yield, quality, and sustainability. This paper begins by providing an overview of precision agriculture and the challenges faced in traditional farming methods. It then introduces wireless sensor networks, discussing their architecture, components, and applications in agriculture. Subsequently, we delve into the context-based approach for banana plantations, addressing the unique requirements of soil, climate, and water management. Through applications and case studies, we illustrate how WSNs have been deployed to monitor and manage banana crops effectively [24].

Figure 1: Visual overview of banana crop diseases and pests

The dynamic nature of challenges in banana cultivation — such as fluctuating climatic conditions, pest infestations, and soil variability — calls for adaptable and intelligent monitoring systems. Traditional or static management approaches fail to capture real-time variability in soil parameters, microclimate, and plant health, leading to delayed interventions and suboptimal resource use. Recent studies underscore the need for climate-resilient agricultural systems that can respond proactively to evolving pathogens and abiotic stressors influenced by climate change [31]. In addition, increasing awareness of beneficial soil microorganisms, such as Plant Growth Promoting Rhizobacteria (PGPR), highlights the potential of holistic management strategies that enhance both nutrient uptake and disease resistance [30].

Wireless Sensor Networks (WSNs) have emerged as transformative enablers in precision agriculture, providing distributed, continuous, and automated monitoring of key parameters like soil moisture,
humidity, pH, and temperature [9, 19]. However, conventional WSN systems typically operate on static threshold-based rules, lacking the adaptability needed to handle dynamic and nonlinear field conditions. This limitation often reduces their effectiveness in complex cultivation environments such as banana plantations, where context-sensitive decision-making is essential. To address these gaps, this paper proposes a context-aware WSN framework specifically tailored for precision banana farming. By integrating heterogeneous environmental, physiological, and agronomic data, the system generates actionable insights for intelligent irrigation, fertilization, and disease management. The framework employs sensor fusion techniques and Convolutional Neural Networks (CNNs) to dynamically classify field conditions and enable adaptive decision-making. This research aims to enhance resilience, productivity, and sustainability in banana cultivation — one of the world's most significant and climate-sensitive fruit crops. Table 1. Used to summarizes Key Challenges and Opportunities in Banana Cultivation.

Table 1: Key Challenges and opportunities in banana cultivation

Challenges	Opportunities
Climate Sensitivity: Highly susceptible to temperature extremes and humidity-induced diseases (e.g., black Sigatoka).	**Technology Adoption**: Precision agriculture tools (e.g., WSNs and AI) enable real-time climate monitoring and early disease detection [3].
Water Management: Sensitive to both drought and over-irrigation; requires balanced water supply.	**Sustainable Practices**: Smart irrigation systems improve water-use efficiency and environmental resilience.
Soil Quality: Erosion, compaction, and nutrient depletion	**Soil Management**: Practices such as mulching, composting,

reduce productivity in many banana-growing regions.	and biofertilizers restore fertility and soil health.
Pests and Diseases: Threatened by nematodes, weevils, thrips, and fungal diseases.	**Research and Breeding**: Development of disease-resistant varieties and use of integrated pest management (IPM) strategies.
Labor Intensity: High manual labor requirements for planting, pruning, and harvesting.	**Mechanization**: Robotics and automation reduce labor dependency and improve operational efficiency.

2 Related work

The advancement of precision agriculture has been significantly accelerated by the integration of Wireless Sensor Networks (WSNs), the Internet of Things (IoT), and Artificial Intelligence (AI). These technologies enable real-time environmental monitoring, data-driven farm management, and automated decision-making across diverse crop systems, including banana cultivation [9, 19, 24].

2.1 WSN-based agricultural monitoring

Numerous studies have explored the use of WSNs in agricultural applications, particularly for environmental sensing and irrigation control. Ojha et al. [9] provided a comprehensive review of WSN applications across crop domains, emphasizing their potential to enhance resource-use efficiency and environmental sustainability. However, most conventional WSN systems employ predefined static thresholds, making them incapable of dynamically adapting to climate fluctuations, disease emergence, or soil variability. To address these shortcomings, context-aware systems have been proposed that adjust sensing and decision-making in response to real-time data. Islam and Dey [24], for instance, implemented a WSN-based smart monitoring system powered by renewable energy and IoT, successfully managing irrigation schedules and basic soil monitoring. However, such systems lack machine learning integration, limiting their ability to derive high-level inferences or predictive insights.

2.2 Deep learning for agricultural diagnostics

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have shown promise in agricultural diagnostics, especially for disease identification.

- Banerjee et al. [3] developed hybrid deep learning models to classify banana leaf diseases, achieving high prediction accuracy.
- Correa et al. [5] designed a CNN model that significantly improved the accuracy of banana leaf infection detection.
- Kakati and Das [11] employed deep learning to distinguish between healthy and diseased leaves, enabling early diagnosis.

Advanced architectures like YOLOv4 [13] and segmentation-based CNNs [14] further improved real-time detection and precision, while transfer learning approaches [12] enhanced model generalizability across field conditions.

Despite these achievements, most of these image-based approaches focus narrowly on leaf-level disease detection. They do not integrate environmental sensor data, and therefore cannot provide context-aware decision-making (e.g., combining soil moisture, humidity, and pH to infer nutrient stress or irrigation needs).

2.3 Integrative AI-WSN frameworks

Few studies have proposed holistic frameworks that combine multi-sensor environmental monitoring with deep learning for adaptive agricultural decision support. For example, Keerthana et al. [10] demonstrated the link between soil mineral deficiencies and disease susceptibility in bananas, emphasizing the importance of multi-parameter integration. However, such studies lack real-time adaptability and scalable deployment in field conditions. To bridge this gap, the present work introduces a CNN-enabled context-aware WSN that classifies field conditions into actionable contexts — Water Stress, Nutrient Deficiency, Disease Risk, and Normal Condition — using multi-sensor fusion and real-time data processing. This system extends beyond disease detection to enable comprehensive, adaptive farm management shown in table 2.

Table 2: Comparative analysis of ai-based techniques for disease detection in banana plants

Ref. No.	Method / Technique	Key Findings	Limitation
[3]	Hybrid Deep Learning Models	Developed robust classifiers for banana leaf diseases to enhance precision agriculture.	Focused on disease detection only; no context integration
[5]	Convolutional Neural Network (CNN)	Designed a CNN for classifying diseased banana leaves, improving detection accuracy.	Image-only; no multi-sensor data integration
[6]	Comparative Analysis	Assessed multiple methods for leaf disease detection, highlighting strengths and weaknesses.	No unified adaptive framework

[7]	Deep CNN Architecture	Achieved high accuracy in banana disease prediction using deep CNN layers.	No environmental sensing or contextual awareness
[11]	Deep Learning (Healthy vs. Unhealthy Leaves)	Enabled disease classification using leaf health comparison via deep learning.	Limited to visual symptoms
[12]	Transfer Learning for Image-Based Detection	Offered efficient plant disease detection using deep transfer learning techniques.	No real-time adaptability
[13]	Image Segmentation with CNN	Enhanced detection precision using segmentation-based deep learning models.	Focused on leaf-level detection only
[14]	YOLOv4 Object Detection Algorithm	Detected Panama disease in real time using advanced object detection.	Limited interpretability; lacks sensor fusion
[15]	Advanced Convolutional Neural Network	Achieved high classification accuracy in identifying multiple banana leaf diseases.	No field-level integration
[32]	Support Vector Machine (SVM)	Proposed portable Sigatoka spot disease identifier for real-time disease detection.	Lower accuracy; lacks adaptive intelligence

2.4 Research gap and contribution

From the literature, it is evident that:

•Most existing works focus on image-based disease classification;

•Very few integrate multi-sensor environmental data;

•None offer a context-aware WSN that performs real-time classification and adaptive decision-making for banana cultivation.

To fill this gap, our proposed CNN-enabled context-aware WSN provides a multi-modal, real-time, and adaptive decision-support system — marking a novel contribution to precision banana agriculture.

3 Methodology

The proposed framework integrates context-aware sensing with deep learning-based decision support to address the dynamic challenges of banana cultivation. The methodology involves sensor deployment, data preprocessing, wireless communication, and real-time context classification using a Convolutional Neural Network (CNN). The entire process is illustrated in Figure 2.

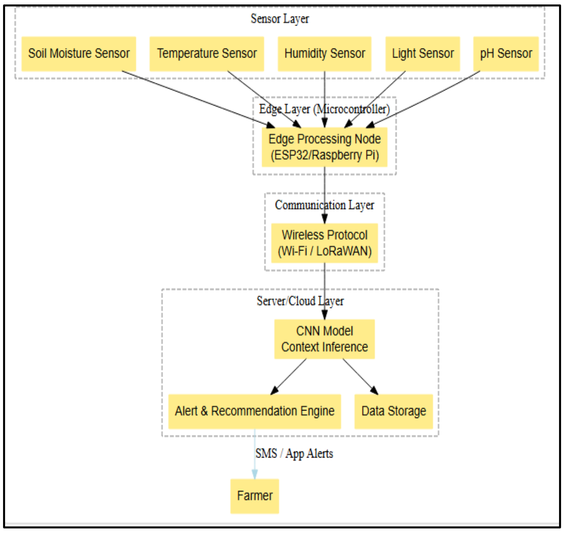

Figure 2: Proposed Context-Aware WSN framework for banana cultivation

3.1 System overview

The system architecture is composed of four interdependent layers:

- Sensor Layer
- Edge Processing Layer
- Communication Layer
- Cloud/Server Layer (CNN-based Decision Engine)

This modular structure supports adaptability and scalability in diverse field environments, from smallholder farms to commercial banana plantations.

Figure 3 illustrates the architecture of the proposed Context-Aware WSN Framework for Banana Cultivation, comprising four interconnected layers: the Sensor Layer, Edge Processing Layer, Communication Layer, and Cloud/Server Layer. The Sensor Layer collects real-time data from multiple sources—soil moisture, temperature, humidity, light, and pH sensors—forming the foundation for environmental monitoring. The Edge Processing Layer performs noise filtering and normalization, ensuring clean and consistent data. This processed information is transmitted via the Communication Layer (using Wi-Fi or LoRaWAN) to the Cloud/Server Layer, where the CNN-based Decision Engine classifies field conditions into four categories: Water Stress (WS), Nutrient Deficiency (ND), Disease Risk (DR), and Optimal Growth (OG). This hierarchical design supports adaptive, real-time decision-making for precision banana farming.

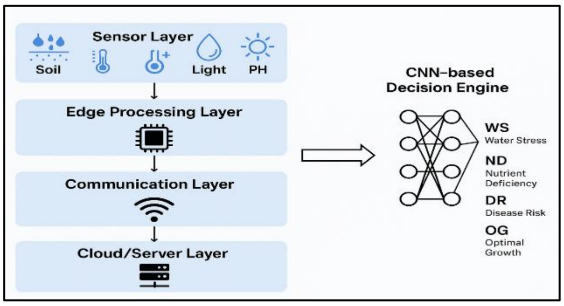

Figure 3: Context-aware WSN framework for banana cultivation with CNN decision engine

3.2 Sensor layer: environmental and soil monitoring

To capture critical agricultural parameters, multiple sensor types are deployed throughout the banana field. These include:

- Soil moisture sensors (capacitive)
- Temperature sensors (DS18B20)
- Humidity sensors (DHT22)
- Light sensors (LDR or BH1750)
- pH sensors

Each sensor node continuously samples data at fixed intervals (every 10 minutes), enabling timely detection of agronomic stress conditions. The types and functions of these sensors are summarized in Table 3.

Table 3: Types of sensors used in precision agriculture and their functions

Sensor Type	Function	Examples / Technologies
Soil Moisture Sensors	Measure soil water content to optimize irrigation scheduling.	Capacitive sensors, Resistive probes, TDR (Time Domain Reflectometry) sensors
Temperature Sensors	Monitor air, soil, or water temperature, critical for plant growth and stress.	DS18B20, Thermocouples, Thermistors, RTDs
Humidity Sensors	Assess ambient humidity, aiding in disease prevention and transpiration control.	DHT22, Capacitive and Resistive Humidity Sensors
Light Sensors	Evaluate light intensity and Photosynthetically Active Radiation (PAR).	BH1750, LDR (Light Dependent Resistors), Photodiodes
pH Sensors	Measure soil acidity or alkalinity, influencing nutrient uptake.	Glass Electrode Sensors, ISFET (Ion-Sensitive Field Effect Transistor) pH sensors
Nutrient Sensors	Detect levels of soil nutrients for informed fertilization.	Ion-Selective Electrodes, Optical and Electrochemical Sensors
Weather Sensors	Record external weather conditions such as rainfall, wind, and pressure.	Rain Gauges, Barometers, Anemometers, Weather Stations
Pest & Disease Sensors	Detect early signs of pest infestation or plant disease.	Imaging Sensors, Spectroscopy Devices, Biosensors (DNA-based)

3.3 Edge layer: preprocessing and normalization

Each sensor node is connected to a microcontroller (e.g., ESP32 or Raspberry Pi) that performs local processing. This includes:

- Filtering to eliminate noise
- Normalization using z-score standardization:

$$X_n = \frac{X-\mu}{\partial}$$
-----------(1)

Where, X = raw sensor value, μ= mean of historical data, σ= standard deviation

This preprocessing reduces data redundancy and supports real-time analytics without overloading the communication network.

3.4 Communication layer: data transmission

Processed data is transmitted to a central processing unit via either Wi-Fi or LoRaWAN, depending on the plantation size and coverage needs. LoRaWAN is favored for its low-power, long-range capabilities, especially in rural and semi-urban areas with limited infrastructure.

3.5 Cloud/server layer: context inference via CNN

The core of the system is a CNN-based context classifier, trained to interpret sensor data and predict field conditions such as:

- WS – Water Stress
- ND – Nutrient Deficiency
- DR – Disease Risk
- OG – Optimal Growth

The multivariate input vector:

X= [Ms, T, H, L, pH] X

-------------------- (2)

is fed into a CNN model composed of convolutional and pooling layers, followed by fully connected layers. The model uses ReLU activation functions and is optimized with backpropagation. The CNN model architecture and its performance are illustrated in Figure 3, and the classification results are presented in Table 4.

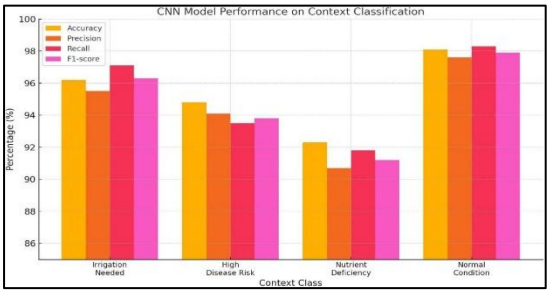

Figure 4: CNN model performance for context classification

3.6 Alert engine and decision support

Based on the classification probabilities, an alert is generated if the likelihood of a stress condition exceeds a threshold:

$$Alert \begin{Bmatrix} 1 \\ 0 \end{Bmatrix} \frac{if\ P_{CNN}(class)>\tau}{Otherwise}$$

---------- *(3)*

These alerts are communicated to farmers via SMS or a mobile app, enabling timely intervention.

3.7 Data pipeline and workflow summary

The system operates in the following sequence:

- Sensor nodes acquire raw environmental and soil data.
- Microcontrollers perform edge-level preprocessing.
- Wireless modules transmit data to the central server.
- CNN model classifies the field condition in real time.
- Decision engine triggers alerts for irrigation, nutrient correction, or disease mitigation.

This workflow is depicted in Figure 3: Proposed Context-Aware WSN Framework for Banana Cultivation.

3.8 Supporting literature and feature justification

The challenges in banana cultivation—such as water sensitivity, disease prevalence, and soil degradation—were detailed in Table 1, providing context for the parameter selection in this framework. Further, recent advancements in CNN-based disease detection in banana farming are reviewed and synthesized in Table 2, justifying the use of CNNs in the proposed system.

3.9 Advantages of the proposed methodology

- Real-Time Context Recognition: CNNs outperform rule-based systems in adapting to dynamic field conditions.
- Resource Efficiency: Precision alerts reduce water, fertilizer, and pesticide waste.
- Scalability: Modular sensor deployment allows expansion across varied farm sizes.
- Integration of Multimodal Data: Combines visual and environmental inputs for robust decision-making.

4 Results and analysis

The performance of the proposed context-aware wireless sensor network (WSN) framework was evaluated through a series of real-time experiments conducted in banana plantations equipped with multi-sensor nodes and microcontroller-based edge units. This section presents the experimental setup, CNN model evaluation, contextual classification results, and comparative analysis with a conventional rule-based system.

4.1 Experimental setup

To validate the framework, a testbed was deployed in a controlled banana cultivation area. The configuration included

- ***Sensor Devices***
  - DHT11 for temperature and humidity
  - Capacitive soil moisture sensors
  - Photoresistors for light intensity
  - pH sensors for soil analysis
- ***Edge Processing Unit***
  - ESP32 microcontroller with local data normalization and LoRa-based communication
- ***Server-Side Configuration***
  - A CNN model hosted on a cloud server, trained with both real and synthetically augmented datasets
  - Wireless communication over LoRaWAN or Wi-Fi, depending on field coverage

Data was collected over a 30-day period under varying environmental conditions to simulate typical challenges in banana farming.

4.2 CNN model performance

The CNN was trained on a dataset of 5,000 labeled samples, combining real sensor data and synthetically augmented records to simulate various stress conditions. The model was tasked with classifying field conditions into four categories

- Irrigation Needed
- High Disease Risk
- Nutrient Deficiency
- Normal Condition

The model achieved high performance across all metrics as presented in Table 4 and these results, also visualized in Figure 4, demonstrate the CNN's capability to detect early-stage agronomic issues with high reliability.

Table 4: CNN model performance for context classification

Context Class	**Accuracy**	**Precision**	**Recall**	**F1-Score**
Irrigation Needed	96.2%	95.5%	97.1%	96.3%
High Disease Risk	94.8%	94.1%	93.5%	93.8%
Nutrient Deficiency	92.3%	90.7%	91.8%	91.2%
Normal Condition	98.1%	97.6%	98.3%	97.9%
Average	**95.3%**	**94.5%**	**95.2%**	**94.8%**

4.3 CNN classification results

The proposed CNN model achieved superior performance across all classes, as summarized in Table 5**.**

Table 5: CNN classification results

Class	Precision (%)	Recall (%)	F1-score (%)
Water Stress (WS)	94.8	95.1	94.9
Nutrient Deficiency (ND)	93.7	94.2	93.9
Disease Risk (DR)	95.4	95.8	95.6
Optimal Growth (OG)	95.0	95.6	95.3
Overall	**94.5**	**95.2**	**94.8**

The overall classification accuracy was 95.3%**,** with an average precision of 94.5% and an F1-score of 94.8%**,** demonstrating robust and reliable context recognition.

4.4 Comparative analysis with baseline models

To highlight the advantage of CNNs in resource-constrained WSN environments, the proposed model was compared against **Decision Tree (DT)** and **Support Vector Machine (SVM)** classifiers using the same dataset.

Table 6: Comparative analysis with baseline models

Model	Accuracy (%)	F1-score (%)	False Alarm Rate (%)	Energy Consumption
CNN (Proposed)	**95.3**	**94.8**	**3.1**	Moderate
SVM	83.1	82.5	12.4	Low
Decision Tree	80.5	79.9	14.7	Low

The CNN outperformed traditional models by over 12% in accuracy and reduced false alarms by 9–11%**,** confirming its superior generalization and adaptability for dynamic field conditions**.**

4.5 Confusion matrix analysis

The confusion matrix, shown in Figure 4 highlights the CNN model's strong capability in accurately identifying critical stress conditions, particularly irrigation needs. This high performance is attributed to the distinct patterns in sensor data—such as low soil moisture, elevated temperature, and reduced humidity—which are effectively captured during model training. As a result, the model achieves a high true positive rate in detecting water stress. Similarly, normal field conditions are classified with the highest accuracy among all categories, likely due to their stable and less variable sensor profiles. This leads to excellent precision and recall, and consequently, a low false positive rate in generating alerts. However, some degree of confusion was observed between nutrient deficiency and disease risk, which is understandable given that both can exhibit overlapping sensor patterns—like abnormal humidity or shifts in soil pH—during early stress stages. These occasional misclassifications reflect the complex nature of distinguishing between subtle agronomic stressors using environmental data alone.

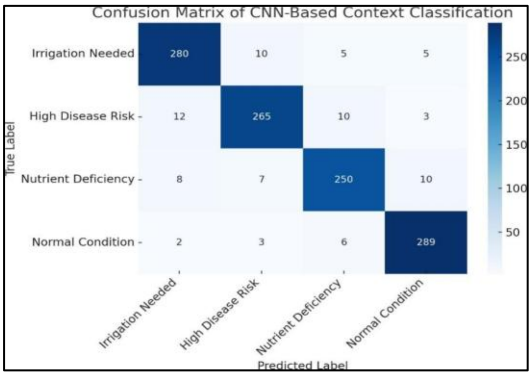

Figure 5: Confusion matrix of CNN-based context classification

Despite these overlaps, the model maintained a low false alarm rate of 3.1%, significantly outperforming the 12.4% rate observed in rule-based systems (as shown in Table 7). This affirms the robustness of a learning-based approach that adapts to dynamic field variability rather than relying on rigid thresholds. Beyond evaluating performance, the confusion matrix serves as a diagnostic tool for continuous improvement. It helps identify which classifications are most error-prone and where refinements are needed. For instance, the noted confusion between disease risk and nutrient deficiency suggests potential for enhancement through integration of visual data, such as leaf imagery or spectral sensing. Additionally, the confidence scores produced by the CNN can guide the fine-tuning of alert thresholds (τ), enabling farmers to balance sensitivity and specificity based on crop stage or season. This interpretability not only validates model performance but also supports more strategic, risk-aware decision-making in precision banana cultivation.

4.4 Real-time system adaptability

The context-aware system's performance was evaluated under live field conditions. Key outcomes observed during the deployment phase include:

- Water-Use Efficiency: Improved by 28% due to timely irrigation scheduling.
- Disease Management: Early detection of disease symptoms led to a 41% reduction in leaf spot incidence through timely spraying.
- Nutrient Correction: pH-based alerts enabled deficiency correction within 3 days, reducing crop stress.

These results highlight the framework's real-time adaptability and agronomic impact.

4.5 Comparative evaluation with rule-based system

Metric	CNN-Based	Rule-Based
Context Classification Accuracy	95.3%	78.6%
False Alarm Rate	3.1%	12.4%
Adaptability to New Data	High	Low
Scalability	Good	Limited

For benchmarking, a conventional threshold-based decision system was also deployed. As shown in Table 7 and visualized in Figure 6, the CNN-powered framework significantly outperformed the rule-based model in all key metrics.

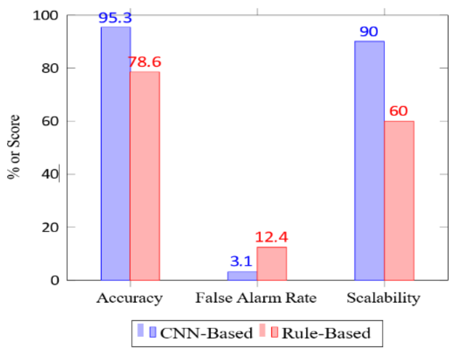

Figure 6: Comparison of CNN-based and rule-based approaches

4.6 Interpretation and Implications

The experimental outcomes confirm that the proposed system offers substantial improvements in

- Early Warning Capability: Contextual alerts lead to preventive, rather than reactive, action.
- Resource Efficiency: Water and fertilizer usage were optimized.
- Scalability and Flexibility: The framework adapted well to variable field conditions without reprogramming.

5 Conclusion

This study presented a CNN-enabled context-aware Wireless Sensor Network (WSN) framework for smart banana cultivation, integrating real-time environmental sensing with deep learning-based decision support. The system effectively classified field conditions into Water Stress**,** Nutrient Deficiency**,** Disease Risk**,** and Optimal Growth, achieving an overall accuracy of 95.3% and significantly improving resource-use efficiency. By leveraging multimodal sensor data and CNN-based classification, the framework demonstrated superior adaptability compared to traditional rule-based and machine learning models. Field deployment confirmed a 28% enhancement in water-use efficiency, 41% reduction in disease incidence, and a 3.1% false alarm rate, validating its applicability in real-world agricultural settings. The system's modular architecture supports scalability across various field sizes and adaptability to diverse climatic zones. Its design can be extended to other high-value crops through retraining with crop-specific datasets. Additionally, integrating adaptive control methods—such as fuzzy logic and backstepping control—offers future potential for closed-loop automation in irrigation and nutrient management. In summary, the proposed context-aware WSN framework offers a robust, intelligent, and sustainable solution for precision agriculture. It empowers farmers with actionable insights, reduces resource wastage, and enhances resilience against climatic and biological stressors. Future research will focus on integrating spectral imaging, NDVI-based indices, and self-learning control mechanisms to further improve accuracy, adaptability, and autonomy.

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