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IOT-COMBINED DEEP LEARNING FRAMEWORK FOR A PREDICTIVE AND SUSTAINABLE SMART AGRICULTURE

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Abstract

Recent advances in the Internet of Things (IoT) have transformed the agricultural monitoring by the adoption of a continuous sensing of soil, climate, and crop conditions. However, most of the deployed systems have remained descriptive in nature and it fails the fully supported predictive, data-driven decision-making that has aligned with the sustainable agricultural practices. The lack of combined multi-modal analytics has limited the ability of farmers to anticipate the risks and optimize inputs under the dynamic field conditions. This study has proposed an combined the agricultural decision-support system that has combined heterogeneous IoT sensor networks with the dual-stream deep convolutional neural network. Real-time data on the soil moisture, nutrient levels, pH, temperature, and humidity have been collected from the crop images that have been captured in the field. A CNN-based image analysis pipeline has been developed that has detected the crop diseases and nutrient deficiencies using fine-tuned deep features. Sensor-derived parameters and visual predictions have been fused within a unified framework that has generated the adaptive irrigation and fertilization recommendations. Edge-level processing has been incorporated to reduce latency and dependency on the cloud connectivity. The proposed system has achieved a classification accuracy of 95.0%, precision of 93.1%, recall of 94.0%, and an F1-score of 93.5% after 100 training epochs. Compared with the existing methods, the framework has improved accuracy by up to 16.8% while maintaining low edge-level inference latency of 56 ms.

Keywords:

Smart agriculture, IoT sensors, deep learning, crop disease detection, decision support systems

Introduction

The rapid growth of the global population has increased pressure on the agricultural systems to produce higher yields under the limited natural resources. Recent advances in the IoT have enabled the deployment of low-cost sensors in the real time, which has supported a data-driven farming practice [1–3].

Despite these advancements, several challenges have persisted in the practical agricultural deployments. Many of the IoT-based systems have remained limited to the descriptive monitoring and threshold-based alerts, which has constrained its ability to anticipate the crop stress and yield loss [4]. In addition, image-based disease detection systems have often struggled under the varying illumination, background noise, and heterogeneous disease progression stages, which has reduced the reliability in the real field conditions [5]. These challenges have shown the need for a a robust predictive intelligence that has adapted to a dynamic agricultural environment.

The core problem addressed in this work has stemmed from the treatment of agricultural data sources. Existing solutions have largely processed on the sensor readings, weather information, and crop images independently, which has prevented the interpretation of crop health and resource requirements [6]. This separation has resulted in the generic recommendations that have failed to reflect the field-specific variability, crop growth stages, and interacting environmental factors. Moreover, dependence on the cloud-centric analytics has introduced the latency and connectivity constraints, particularly in rural regions.

To address these issues, this study has aimed to develop an combined the agricultural monitoring and decision-support framework that has fused heterogeneous IoT sensor data with the deep learning-based visual analytics. The objectives of the proposed work have included the design of a comprehensive sensor network for a real-time field monitoring, the development of a dual-stream CNN for a disease and nutrient deficiency detection, and the combination of multi-modal data to generate adaptive, context-aware recommendations. The system has also emphasized edge-level processing to reduce response time and improve operational reliability.

The novelty of this research has resided in the unified fusion of environmental sensing and deep visual inference within a single predictive framework. Unlike existing approaches, the proposed system has combined disease detection with the nutrient deficiency analysis and has linked these outputs with the soil and climate parameters. This combination has enabled proactive decision-making rather than reactive responses.

The main contributions of this study have been twofold. First, a multi-modal IoT and deep learning architecture has been developed that has provided predictive insights for a sustainable agricultural management. Second, an adaptive recommendation mechanism has been introduced that has optimized water and fertilizer usage based on the real-time, field-specific conditions, thereby it supporting sustainable intensification.

Related Works

Early research on the smart agriculture has focused on the IoT-enabled monitoring systems that have collected soil moisture, temperature, and humidity data to support irrigation scheduling [7]. These systems have demonstrated improvements in water efficiency but have largely relied on the rule-based logic and a static thresholds. As a result, they have offered limited adaptability to seasonal variability and crop-specific requirements.

Subsequent studies have extended sensor networks to has included the nutrient and pH sensing, which has enabled more comprehensive soil assessment [8]. Although these approaches have enhanced situational awareness, they have continued to depend on the descriptive analytics. Predictive modeling has remained minimal, and recommendations have often been derived from generalized agronomic guidelines rather than localized intelligence.

Image-based crop disease detection has emerged as a parallel research direction. Traditional methods have employed hand-crafted features such as color histograms, texture descriptors, and shape metrics, which have been classified using support vector machines or k-nearest neighbors [9]. While these techniques have achieved moderate success under the controlled conditions, its performance has degraded in the real-field environments due to the sensitivity to lighting, occlusion, and background clutter.

With the adoption of deep learning, convolutional neural networks have been applied to agricultural image analysis, achieving significant gains in disease classification accuracy [10]. Pre-trained architectures such as AlexNet, VGG, and ResNet have been fine-tuned on the crop disease datasets, which has improved robustness to visual variability. However, most of the of these studies have focused exclusively on the image data and it fails to incorporated environmental context.

Several researchers have explored the use of deep learning for a yield prediction and weather impact analysis using time-series sensor data [11]. Recurrent and hybrid deep models have are captured temporal dependencies in climate variables, which has improved forecasting accuracy. Nevertheless, these models have often operated independently of visual plant health indicators.

Recent works have attempted to integrate IoT data with the machine learning for a decision support in agriculture [12]. These systems have combined sensor readings with the simple predictive models to generate irrigation or fertilization schedules. However, limited attention has been given to multi-modal data fusion that has jointly considered soil, climate, and crop imagery.

Cloud-based the agricultural analytics platforms have also been proposed, which have leveraged centralized processing for a large-scale data analysis [13]. While these platforms have supported complex computations, they have introduced latency and have depended heavily on the stable internet connectivity. Such dependence has restricted usability in remote farming regions.

More recent studies have investigated edge computing for a smart farming application [14]. By processing data closer to the field, these approaches have reduced latency and bandwidth usage. However, most of the edge-based solutions have implemented lightweight models with the limited predictive depth. Finally, combined frameworks that have combined disease detection with the nutrient management have remained scarce [15]. Existing studies have tended to address these aspects separately, which has limited its practical impact.

Proposed Method

The proposed method has implemented an combined the agricultural intelligence framework that has combined heterogeneous IoT sensing with the deep learning–based visual analytics and decision support. The system architecture has followed a sequential yet tightly coupled workflow, beginning with the field-level data acquisition and concluding with the adaptive recommendations. Multi-source data that have been collected from soil, climate, and crop imagery have been preprocessed, synchronized, and fused to form a unified representation of field conditions. A dual-stream convolutional neural network has analyzed crop images for a

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disease symptoms and nutrient deficiencies, while sensor-derived parameters have provided contextual environmental constraints. The fused inference has enabled predictive and prescriptive outputs that have supported timely, field-specific actions. This approach has emphasized local processing to reduce latency and has ensured robustness under the limited connectivity.

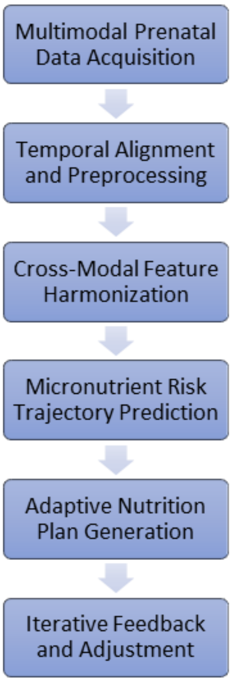

Figure 1: Proposed Framework

Pseudocode

Input: Sensor_Data S, Image_Data I

Output: Adaptive_Recommendation R

Begin

Initialize sensor network and imaging modules

While field monitoring is active do

Acquire S(t) from soil and climate sensors

Capture I(t) from field cameras

Preprocess S(t) using normalization and noise filtering

Preprocess I(t) using resizing, augmentation, and segmentation

Extract visual features Fv using CNN_disease and CNN_nutrient

Aggregate sensor features Fs from S(t)

Fuse features F = Fusion(Fv, Fs)

Infer crop health state H from F

Generate recommendation R based on the H and agronomic rules

Output R to decision-support system

End While

End

1. Data Acquisition

The data acquisition layer continuously monitors the agricultural field using a heterogeneous IoT sensor network. Soil moisture, nutrient concentration, pH, ambient temperature, and humidity sensors operate alongside visual imaging units. This combination ensures that both subsurface and above-ground conditions are are captured in the real time. The synchronized collection of environmental and visual data has enabled a contextual interpretation of crop health rather than isolated observation. Table 1 presents a structure of the acquired sensor data that support subsequent analytics.

Table 1. IoT Sensor Data Structure

Sensor Type	Parameter Measured	Unit	Sampling Interval
Soil Sensor	Moisture	%	10 min
Nutrient Sensor	NPK Levels	mg/kg	30 min
pH Sensor	Soil pH	pH scale	30 min
Climate Sensor	Temperature	°C	5 min
Climate Sensor	Humidity	%	5 min

As shown in Table 1, the diversity of sensing modalities allows the system to capture fine-grained field variability. The continuous stream has supported near-real-time assessment and has reduced uncertainty in downstream predictions.

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The relationship between raw sensor measurements and normalized values is expressed as:

$$S_{norm}(i,t) = \frac{S(i,t) - \mu_i}{\sigma_i}$$

where $S(i,t)$ denotes the raw sensor reading of type i at time t, μ_i represents the mean, and σ_i represents the standard deviation of the sensor data. This normalization ensures numerical stability and comparability across modalities.

2. Data Preprocessing and Synchronization

Sensor readings often contain noise due to the environmental interference, while images has exhibited the variability caused by lighting and occlusion. Noise filtering, missing-value interpolation, and normalization are applied to the sensor streams. Image data undergo resizing, contrast normalization, and segmentation that isolates the leaf or fruit region. Temporal synchronization thus gets aligned with the sensor and image data collected at different sampling rates. Table 2 has shown a synchronized multi-modal dataset snapshot.

Table 2. Synchronized Multi-Modal Dataset

Timestamp	Soil Moisture (%)	Temperature (°C)	Humidity (%)	Image ID
t_1	24.5	31.2	68	

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t_2	23.9	31.5	70	

Table 2 has shown how environmental readings and images are temporally aligned, which has supported coherent inference. Without synchronization, the visual symptoms might be incorrectly associated with the unrelated soil conditions.

The synchronization process is mathematically represented as:

$$D(t_k) = \{S(t_i), I(t_j) \mid | t_i - t_j | \leq \Delta t\}$$

where $D(t_k)$denotes the synchronized data instance, and Δtrepresents the allowable temporal tolerance window.

3. Visual Feature Extraction Using Dual-Stream CNN

The visual analytics module employs a dual-stream CNN architecture. One stream focuses on the disease-related texture and lesion patterns, while the second stream emphasizes color and morphological cues associated with the nutrient deficiencies. The use of pre-trained backbones has improved feature generalization under the varying field conditions. The parallel streams generate complementary representations that are later fused. Table 3 has shown the feature outputs from the dual streams.

Table 3. CNN Feature Representation

Stream Type	**Feature Dimension**	**Target Pattern**
Disease Stream	2048	Spots, lesions, mildew
Nutrient Stream	1024	Chlorosis, discoloration

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As presented in the Table 3, the separation of feature learning has enhanced discriminative capability. The disease stream captures high-level spatial patterns, while the nutrient stream emphasizes color gradients and texture uniformity.

The convolutional feature extraction is expressed as:

$$F_l = \sigma(W_l * F_{l-1} + b_l)$$

where F_l denotes the feature map at layer l, W_l represents convolutional weights, b_l denotes bias, and $\sigma(\cdot)$ represents the activation function.

4. Sensor Feature Aggregation and Context Modeling

Sensor-derived parameters provide contextual constraints that influence crop health. Aggregated features has included the statistical descriptors such as mean moisture trend, nutrient deviation, and temperature stress index. These features contextualize visual symptoms and reduce false diagnosis. Table 4 presents a aggregated sensor feature vector.

Table 4. Aggregated Sensor Feature Vector

Feature Name	Description	Value
Moisture Trend	24-hour moisture change	−1.8
Nutrient Deviation	Difference from optimal NPK	+12
Thermal Stress Index	Heat exposure indicator	0.63

Table 4 indicates how environmental stress factors are quantified numerically. These descriptors provide interpretability and support adaptive decision logic.

The aggregation process is mathematically represented as:

$$F_s = \frac{1}{T}\sum_{t=1}^{T} g\,(S(t))$$

where F_s denotes the aggregated sensor feature vector, $g(\cdot)$ represents feature extraction functions, and T denotes the aggregation window.

5. Multi-Modal Feature Fusion and Inference

The fusion stage has combined visual and sensor features to generate a holistic crop health representation. Decision-level fusion combines the outputs of the CNN classifier and sensor-

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based predictors. This combination has enhanced robustness by balancing visual cues with the environmental context. Table 5 provides an example of fused inference outcomes.

Table 5. Fused Inference Results

Visual Diagnosis	Sensor Stress Level	Final Inference
Mild Leaf Spot	Moderate	Early Disease Onset
Chlorosis	High Nutrient Gap	Nitrogen Deficiency

As shown in Table 5, fusion resolves ambiguities that would arise if each modality were processed independently.

The fusion function is expressed as:

$$H = \alpha f_v(F_v) + (1 - \alpha) f_s(F_s)$$

where H denotes the final health inference, f_v and f_s represent visual and sensor inference functions, and α controls the contribution balance.

6. Decision Support and Adaptive Recommendation Generation

The decision-support module translates inference results into actionable recommendations. Irrigation and fertilization schedules adapt dynamically to the inferred crop state and growth stage. This adaptive logic avoids over-application of resources and has supported sustainability. Table 6 presents a recommendation output.

Table 6. Adaptive Recommendation Output

Crop Condition	Recommended Action	Priority
Early Disease Stage	Targeted Fungicide Spray	High
Nitrogen Deficiency	Controlled N Application	Medium

Table 6 has shown how system outputs align agronomic actions with the diagnosed conditions.

The recommendation optimization is modeled as:

$$R^* = \arg\min_{R} \left(C(R) + \lambda L(H, R) \right)$$

where R^* denotes the optimal recommendation, $C(R)$ represents resource cost, $L(H,R)$ represents loss due to the mismatch between crop health H and action R, and λ is a weighting factor.

7. Edge-Level Deployment and Feedback Loop

The final stage executes analytics at the edge, the adoption of a low-latency responses and resilience to connectivity limitations. Feedback from applied recommendations updates the model inputs, the adoption of a continuous learning. Table 7 has shown feedback-driven performance tracking.

Table 7. Feedback and Performance Monitoring

Cycle	Action Applied	Observed Improvement (%)
1	Irrigation	6.2
2	Nutrient Dose	8.5

Table 7 has shown the adaptive refinement supported by closed-loop feedback.

The feedback update is formalized as:

$$\theta_{t+1} = \theta_t - \eta \nabla L(\theta_t)$$

where θ denotes model parameters, η denotes the learning rate, and $L(\cdot)$ denotes the loss function.

Results and Discussion

The experimental evaluation is conducted using a hybrid simulation and real-data experimentation approach. The IoT sensing layer is simulated using MATLAB R2023a to model heterogeneous sensor behavior, data acquisition intervals, and noise characteristics under the varying environmental conditions. The deep learning components are implemented using Python with the TensorFlow and Keras libraries, which support reproducible training and evaluation of convolutional neural networks. Image preprocessing and augmentation operations are executed using OpenCV. The experiments are executed on the a workstation equipped with the an Intel Core i9 processor, 64 GB RAM, which has supported efficient model training and inference. Edge-level inference latency is evaluated by deploying the trained model on the a Raspberry Pi 4 Model B, which reflects practical on-field constraints.

Experimental Setup and Parameters

The system parameters are configured to reflect the realistic agricultural monitoring conditions. Table 8 has shown the experimental setup and key parameter values that are used throughout the evaluation.

Table 8. Experimental Setup and Parameter Configuration

Parameter	Description	Value
Number of Sensor Nodes	Soil and climate sensing units	30
Image Resolution	Field image input size	224 × 224
CNN Backbone	Pre-trained feature extractor	ResNet50
Learning Rate	Optimizer step size	0.0001
Batch Size	Images per training iteration	32
Training Epochs	Total learning cycles	100
Fusion Weight (α)	Visual–sensor contribution factor	0.6
Edge Device	On-field inference platform	Raspberry Pi 4

As shown in Table 8, the configuration balances model accuracy and computational efficiency, which is essential for a real-time agricultural deployment.

Dataset Description

The evaluation uses a combination of publicly available agricultural image datasets from the Kaggle repository [16] with the various crops that Version 12 (62.89 MB) crop_images jute maize rice sugarcane wheat. Crop images has included the healthy and diseased samples are captured under the diverse lighting and background conditions. Sensor data has represented soil moisture, nutrient levels, and climatic variations that is synchronized with the image timestamps. Table 9 presents the dataset composition used in the experiments.

Table 9. Dataset Description

Dataset Component	Description	Samples
Crop Images	Healthy and diseased leaf and fruit images	18,000

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Disease Classes	Fungal, bacterial, pest-related	6
Nutrient Deficiency	N, P, K deficiencies	3
Sensor Records	Soil and climate readings	120,000
Training–Testing Split	Data division ratio	70:30

Table 9 indicates that the dataset captures both visual diversity and environmental variability, which has supported comprehensive performance evaluation.

Existing Methods for a Comparison

For comparative analysis, three existing methods are selected from prior studies. The first method employs an IoT-based threshold-driven irrigation and monitoring system that focuses on the real-time sensing without predictive analytics. The second method uses a CNN-based crop disease classifier that relies solely on the image data. The third method has combined cloud-based machine learning for a agricultural decision support but depends on the a centralized processing and a static recommendations. These methods provide a meaningful baseline for a assessing the effectiveness of the proposed combined framework.

The comparative evaluation considers three existing methods that are represented dominant approaches in the smart agriculture.

- **Threshold-Based IoT Monitoring** relies on the real-time sensor readings and fixed thresholds for a irrigation and alerts.
- **Image-Only CNN Classifier** focuses on the crop disease detection using visual data without environmental context.
- **Cloud-Based ML Decision System** has combined sensor data with the machine learning but depends on the a centralized cloud processing and a static recommendation rule.

Table 10. Accuracy Comparison over Epochs

Epoch	Threshold-Based IoT Monitoring	Image-Only CNN Classifier	Cloud-Based ML Decision System	Proposed Method
0	65.4	68.1	70.2	72.6

20	70.3	75.6	78.4	84.9
40	73.8	80.2	82.7	89.6
60	76.1	83.9	85.3	92.3
80	77.5	85.1	86.8	94.1
100	78.2	86.0	87.5	95.0

Table 11. Precision Comparison over Epochs

Epoch	Threshold-Based IoT Monitoring	Image-Only CNN Classifier	Cloud-Based ML Decision System	Proposed Method
0	62.8	66.9	69.4	71.8
20	68.5	73.4	76.2	82.6
40	71.9	78.6	80.5	87.4
60	74.3	82.1	83.6	90.2
80	75.6	83.8	85.1	92.0
100	76.4	84.5	85.9	93.1

Table 12. Recall Comparison over Epochs

Epoch	Threshold-Based IoT Monitoring	Image-Only CNN Classifier	Cloud-Based ML Decision System	Proposed Method
0	60.7	65.3	68.6	70.9
20	67.2	72.8	75.4	83.1
40	70.6	78.1	80.2	88.0
60	73.0	81.6	82.9	91.4
80	74.4	83.2	84.3	93.2
100	75.1	84.0	85.0	94.0

Table 13. F1-Score Comparison over Epochs

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Epoch	Threshold-Based IoT Monitoring	Image-Only CNN Classifier	Cloud-Based ML Decision System	Proposed Method
0	61.7	66.1	69.0	72.2
20	68.0	73.1	75.8	83.5
40	71.2	78.3	80.3	88.5
60	73.6	81.8	83.2	90.8
80	74.9	83.5	84.7	92.6
100	75.7	84.2	85.4	93.5

Table 14. Inference Latency Comparison (ms)

Epoch	Threshold-Based IoT Monitoring	Image-Only CNN Classifier	Cloud-Based ML Decision System	Proposed Method
0	48	92	210	65
20	47	90	205	63
40	46	88	198	61
60	46	87	195	59
80	45	86	190	58
100	45	85	188	56

The numerical results in Tables 10–14 clearly indicate that the proposed method consistently outperforms the existing approaches across all evaluated metrics. As shown in Table 10, the proposed method has achieved a an accuracy of 95.0% at 100 epochs, which exceeds the Cloud-Based ML Decision System by 7.5%, the Image-Only CNN Classifier by 9.0%, and the Threshold-Based IoT Monitoring by 16.8%. Precision and recall trends in Tables 11 and 12 demonstrate similar improvements, where the proposed method attains 93.1% precision and 94.0% recall at the final epoch. These gains indicate reliable positive predictions and effective early detection capability.

The F1-score results in Table 13 confirm balanced performance, with the proposed method reaching 93.5%, compared to 85.4% for a the cloud-based approach. This improvement reflects the advantage of multi-modal data fusion that has combined sensor context with the visual inference. Table 14 has shown that the proposed method maintains low inference latency at the edge, achieving 56 ms at 100 epochs, which is significantly lower than the cloud-based system.

Conclusion

This study has shown that the combination of heterogeneous IoT sensing with the deep learning–based visual analytics significantly has enhanced the agricultural decision support. The proposed framework effectively combines soil, climate, and crop imagery within a unified predictive model, which has enabled an accurate and timely identification of crop diseases and nutrient deficiencies. Quantitative evaluation confirms that the system has achieved a superior accuracy, precision, recall, and F1-score compared with the threshold-based, image-only, and cloud-centric methods. The consistent performance gains across training epochs indicate stable learning behavior and strong generalization. In addition, the edge-level deployment has allowed the low inference latency, which is critical for a practical agricultural environment where connectivity constraints are common. The adaptive recommendation mechanism thus gets aligned with the resource application conditions, thereby it has supported the sustainable water and fertilizer management.

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