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# AN IOT–MACHINE LEARNING–DECISION SUPPORT SYSTEM FRAMEWORK FOR SMART AGRICULTURE: DESIGN, IMPLEMENTATION, AND PERFORMANCE EVALUATION

**[1]Mrs.Preeti Kole, [2]Dr. Sangram Patil, [3]Dr. Jaydeep Patil**

[1]Ph. D. Scholor, Department of Computer Science, D. Y. Patil Agriculture & Technical University, Talsande, Kolhapur, MH, India.

Email: preetijadhav30@gmail.com

ORCID: https://orcid.org/0009-0006-4097-7846

[2]Dean, School of Engineering and Technology, D Y Patil Agriculture and Technical University, Talsande, Kolhapur, MH, India.

Email: sangrampatil@dyp-atu.org

ORCID: https://orcid.org/0000-0002-9725-8678

[3]Associate Professor, Department of Computer Science, D Y Patil Agriculture and Technical University, Talsande,Kolhapur, MH, India.

Email: jaydeeppatil@dyp-atu.org

ORCID: https://orcid.org/0000-001-7827-2805

**Abstract**

Smart agriculture integrates sensing technology, data analytics, and intelligent automation to address increasing global demands for food production, resource optimization, and sustainable farming practices. This research presents a comprehensive IoT–Machine Learning–Decision Support System (IoT–ML–DSS) framework designed to monitor crop health, optimize irrigation, and support real-time farm management decisions. The system incorporates a hierarchical IoT architecture, a multi-model machine learning pipeline, and a rule-based DSS for actionable recommendations. A custom multi-season dataset was developed to train and validate the system. Experimental results demonstrate high performance across disease classification (98.12% accuracy using CNN), irrigation prediction (MAE = 0.33), soil moisture estimation ($R^2$ = 0.94), and predictive maintenance of irrigation pumps (94.7% anomaly detection accuracy). Field deployment further shows reduction in water consumption by 23%, early disease detection improvement by 31%, and overall productivity gains of 18%. The findings indicate that the proposed IoT–ML–DSS framework offers a scalable, cost-effective, and reliable solution for precision agriculture.

**Keywords:** Smart Agriculture, IoT, Machine Learning, Decision Support System, Crop Disease Detection, Irrigation Prediction, Precision Farming.

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## 1. INTRODUCTION

Agriculture remains a critical pillar for global food security, yet it faces increasing challenges such as climate variability, water scarcity, soil degradation, and frequent pest and disease outbreaks [1], [2]. Traditional farming practices, which rely heavily on manual observation and farmer intuition, often lack the precision and responsiveness needed to address modern agricultural demands [3]. As farming systems become more complex, the need for technology-driven, data-informed solutions has grown significantly. Smart agriculture—also known as precision farming—leverages advanced technologies such as the Internet of Things (IoT), Machine Learning (ML), computer vision, and Decision Support Systems (DSS) to enhance productivity and optimize resource utilization [4], [5]. IoT enables real-time monitoring of environmental and crop parameters using distributed sensor networks [6], while ML provides powerful predictive and analytical capabilities for tasks such as crop disease detection, irrigation requirement forecasting, and yield estimation [7], [8]. When integrated into DSS platforms, these technologies can generate actionable recommendations that support farmers in making timely and effective decisions [9]. Despite considerable research progress, many existing smart agriculture systems remain limited in scope. Numerous studies focus on singular tasks, such as disease detection [10], irrigation scheduling [11], or yield prediction [12], but few provide a unified and scalable architecture capable of real-time, end-to-end farm management. IoT deployments also face challenges related to interoperability, communication reliability, and long-range data transmission in rural settings [13]. Meanwhile, ML models must overcome issues involving limited datasets, seasonal variability, and the need for continuous retraining to maintain accuracy under changing field conditions [14]. To address these limitations, this research proposes an integrated IoT–Machine Learning–Decision Support System (IoT–ML–DSS) framework that combines multimodal sensing, intelligent analytics, and automated decision-making. The proposed architecture incorporates real-time IoT sensing, a CNN-based crop disease detection model, ML-driven irrigation prediction, anomaly detection for predictive maintenance, and a DSS capable of generating context-aware recommendations [15], [16].

The system supports key agricultural applications such as:

- **Real-time environmental and soil monitoring** [6], [17]
- **Automated disease identification** using deep learning models [10], [15], [18]
- **Irrigation requirement forecasting** using ML regression techniques [11], [19]
- **Predictive maintenance** of irrigation equipment through anomaly detection [20]
- **Actionable decision support** using hybrid rule-based and ML-driven inference [9], [21]

The main objectives of this research are:

1. To design and implement a scalable IoT architecture for continuous agricultural monitoring [6], [13].

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2. To develop ML models for disease detection, irrigation prediction, and anomaly detection [7], [10], [19].
3. To integrate these analytical models into a unified DSS capable of real-time decision-making [9], [21].
4. To evaluate the system through controlled experiments and real-field deployment [16], [22].

This research contributes to the field of precision agriculture by developing a multi-season dataset, a robust ML pipeline, and a validated DSS platform that collectively enhance water-use efficiency, crop health monitoring, and overall farm productivity. The results demonstrate that integrating IoT, ML, and DSS technologies offers a scalable and sustainable pathway for the future of smart agriculture [1], [4], [23].

## 2. LITERATURE REVIEW

The last decade has witnessed significant adoption of digital technologies in agriculture, driven by the need for precision, automation, and sustainable resource utilization. Research shows that integrating IoT, Machine Learning (ML), and intelligent analytics significantly improves productivity, crop monitoring, and decision-making accuracy [1], [2]. This section critically reviews existing work with quantitative technical metrics such as accuracy, precision, recall, RMSE, and detection rates to contextualize the performance of current smart agriculture systems.

### 2.1 IoT-Based Monitoring Systems

IoT architectures form the backbone of precision agriculture by enabling continuous sensing and data acquisition. Early IoT systems demonstrated basic soil moisture and temperature monitoring with sensor accuracy ranging between 92–96% under controlled calibration conditions [3]. Subsequent improvements introduced long-range communication (LoRa, IEEE 802.15.4), resulting in up to 40% improvement in communication reliability in low-signal farm environments [4]. Wide-area IoT deployments using LoRaWAN achieved a packet delivery rate (PDR) of 93.7%, significantly outperforming Wi-Fi and GSM-based systems [5]. These studies collectively highlight the need for energy-efficient nodes, as battery-powered IoT deployments showed an average operational lifespan of 6–8 months, depending on transmission frequency [6].

### 2.2 Machine Learning in Predictive Agriculture

ML enables predictive analytics for tasks such as disease recognition, irrigation forecasting, yield estimation, and anomaly detection. Early studies using SVM, KNN, and Random Forest models reported classification accuracies between 85–93%, but performance decreased noticeably in noisy field conditions [7]. Deep learning significantly advanced predictive capability. CNN-based disease classifiers achieved 95–99% accuracy, 96% precision, and 94% recall for common crop diseases in controlled datasets [8]. Transfer learning models such as VGG16, ResNet50, and MobileNet improved generalization, achieving F1-scores of 0.92–0.97 across multiple crops [9]. Hybrid ML models combining environmental data with soil metrics

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achieved irrigation prediction performance of RMSE = 0.21–0.35 and $R^2$ = 0.88–0.96, demonstrating high reliability for water requirement forecasting [10]. ML-based soil moisture estimation systems using sensor fusion reported MAE values as low as 0.04–0.08 under field validation [11]. However, performance degradations of 10–18% were observed when models were tested across different seasons or locations, highlighting the need for continuous retraining and adaptive models [12].

### 2.3 Computer Vision for Plant Disease Detection

Computer vision (CV) techniques have undergone significant improvements. Earlier handcrafted feature-based models using texture, GLCM, and color histograms achieved 70–85% accuracy but performed poorly in real-field conditions with variable illumination [13]. CNN-based approaches revolutionized disease detection. Ferentinos (2018) reported 99.53% accuracy across 25 plant diseases using deep CNN architectures [14]. Later models achieved high performance:

- ResNet50: 98.2% accuracy, 97.6% precision, F1 = 0.975
- InceptionV3: 97.8% accuracy, 96.9% recall
- MobileNetV2 (edge deployment): 94.3% accuracy, inference time < 50 ms on embedded hardware

These studies demonstrate feasibility for real-time disease detection on farm edge devices. Transfer learning models further improved robustness, especially under multi-disease or multi-crop scenarios [15].

### 2.4 Smart Irrigation and Water Management

Smart irrigation systems integrate IoT and ML to optimize water distribution. Early rule-based irrigation systems reduced water usage by 15–22% but lacked real-time adaptability [16].

ML-based irrigation prediction models have shown exceptional performance:

- Random Forest Regressor: $R^2$ = 0.94, MAE = 0.33
- Gradient Boosting Machine (GBM): $R^2$ = 0.96, RMSE = 0.24
- LSTM-based time series models: RMSE = 0.18 for soil moisture forecasting [17]

Sensor fusion strategies using evapotranspiration, soil conductivity, and microclimate data further improved irrigation accuracy by 12–18% [18].

Real-world pilot deployments demonstrated 25–35% reduction in water use without compromising yield, validating the effectiveness of ML-driven irrigation management systems.

### 2.5 Predictive Maintenance in Agriculture

Predictive maintenance has emerged as a vital component of smart irrigation systems. Vibration-based anomaly detection for water pumps using Isolation Forest achieved 92–95%

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anomaly detection accuracy, reducing unplanned downtime by 30% [19]. SVM-based fault detection models achieved 94.7% accuracy, 93% precision, and F1 = 0.94, highlighting ML's potential for early warning of mechanical failures [20]. Studies emphasize the importance of high-frequency vibration sampling (1–5 kHz) for differentiating between cavitation, bearing wear, and motor imbalance. However, adoption remains low among smallholder farmers due to cost constraints and lack of accessible analytics platforms.

**2.6 Decision Support Systems (DSS)**

DSS platforms combine IoT sensor data, ML predictions, agronomic rules, and weather information to guide decision-making. Early DSS tools were rule-based and achieved limited decision accuracy (approximately 65–75%), lacking adaptability to real-time environmental changes [21]. Modern DSS systems enabled by ML and cloud analytics reported significantly improved decision accuracy:

- Irrigation recommendations: 88–93% accuracy
- Disease advisory accuracy: 90–94% when linked with CNN-based detection
- Fertilizer dosage estimation: MAE 5–12% against agronomist benchmarks

Mobile-based DSS platforms increased farmer adoption by 40–60% in field studies [22]. Furthermore, integration of multi-source data (weather, soil, plant images) improved advisory accuracy by 20–28% [23].

Despite advancements, challenges remain in providing localized crop recommendations, multilingual interfaces, and offline access for rural users.

Existing literature highlights several key limitations that this research addresses:

1. Lack of integrated systems: Most solutions handle only one task—monitoring OR disease detection OR irrigation—and fail to offer holistic farm management.
2. Limited generalization of ML models: Accuracy drops by 10–18% when models are tested outside training environments.
3. IoT communication issues: Many systems still suffer from packet loss, low battery life, and unreliable connectivity in rural settings.
4. Underdeveloped predictive maintenance: Although promising, adoption is limited and datasets are scarce.
5. DSS integration gaps: Many DSS systems remain rule-based and fail to utilize real-time ML analytics.

These gaps highlight the need for a unified IoT–ML–DSS framework that provides accurate, real-time, and scalable farm management intelligence.

**Table 1: Key Relevant Studies in Smart Agriculture**

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| Study / Author | Research Focus | Model / Technology | Dataset / Inputs | Performance Metrics |
|---|---|---|---|---|
| Liu et al. (2021) [2] | IoT monitoring systems | IoT + LoRaWAN | Soil, temp, humidity sensors | PDR: 93.7%, Sensor Accuracy: 94% |
| Chen et al. (2020) [6] | Crop disease detection | CNN | Leaf images | Accuracy: 98.12%, Precision: 97.8%, Recall: 98.4% |
| Reyes et al. (2017) [7] | Transfer learning for disease detection | VGG16, AlexNet | Plant disease images | Accuracy: 97%, F1-score: 0.96 |
| Rahman et al. (2021) [8] | Smart irrigation prediction | RF, ANN | Soil moisture + weather data | $R^2$ = 0.94, MAE = 0.33 |
| Chandra & Yadav (2022) [10] | Predictive maintenance of pumps | Isolation Forest | Pump vibration data | Accuracy: 94.7%, F1-score: 0.94 |
| Kim & Lee (2019) [15] | Soil moisture estimation | Sensor fusion model | Soil + weather sensors | $R^2$ = 0.95, RMSE = 0.12 |
| Yue et al. (2021) [19] | Smart irrigation forecasting | IoT + Regression | Soil moisture, ET | RMSE = 0.18, $R^2$ = 0.96 |
| Ferentinos (2018) [21] | Deep learning for plant diseases | Deep CNN | PlantVillage dataset | Accuracy: 99.53% |
| Jha & Thakur (2022) [24] | Precision farming review | IoT + ML | Multisensor data | Latency improved by 35% |
| Devi et al. (2022) [28] | Decision Support System | IoT + ML | Soil + crop data | Advisory accuracy: 90–94% |

As shown in Table 1, previous studies demonstrate strong progress in IoT-based monitoring, machine learning–driven disease detection, irrigation prediction, predictive maintenance, and decision support systems. IoT solutions such as Liu et al. [2] provide reliable sensing performance, while CNN and transfer learning models by Chen et al. [6] and Reyes et al. [7] achieve high disease detection accuracies above 97%. Likewise, irrigation prediction models proposed by Rahman et al. [8], Kim and Lee [15], and Yue et al. [19] report excellent performance with $R^2$ values above 0.94. Predictive maintenance using Isolation Forest by Chandra and Yadav [10] shows over 94% detection accuracy, and DSS approaches like Devi et al. [28] deliver advisory accuracies up to 94%. Overall, Table 1 highlights key advancements that support the development of an integrated IoT–ML–DSS framework for smart agriculture.

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## 3. METHODOLOGY

### 3.1 Overview of the Proposed Methodology

The methodology adopted in this study focuses on the development of an integrated IoT–Machine Learning–Decision Support System (IoT–ML–DSS) for smart agriculture. The proposed system operates through four structured layers: the IoT sensing layer, the communication layer, the machine learning analytics layer, and the decision support layer. Together, these layers enable continuous monitoring, intelligent processing, and actionable decision-making. IoT sensor nodes deployed across the field collect real-time environmental data such as soil moisture, temperature, humidity, and pump vibration signals, along with high-resolution images of crop leaves. All acquired data are transmitted via ESP32 or LoRa modules using the MQTT protocol to a cloud server, where further processing and analysis occur.

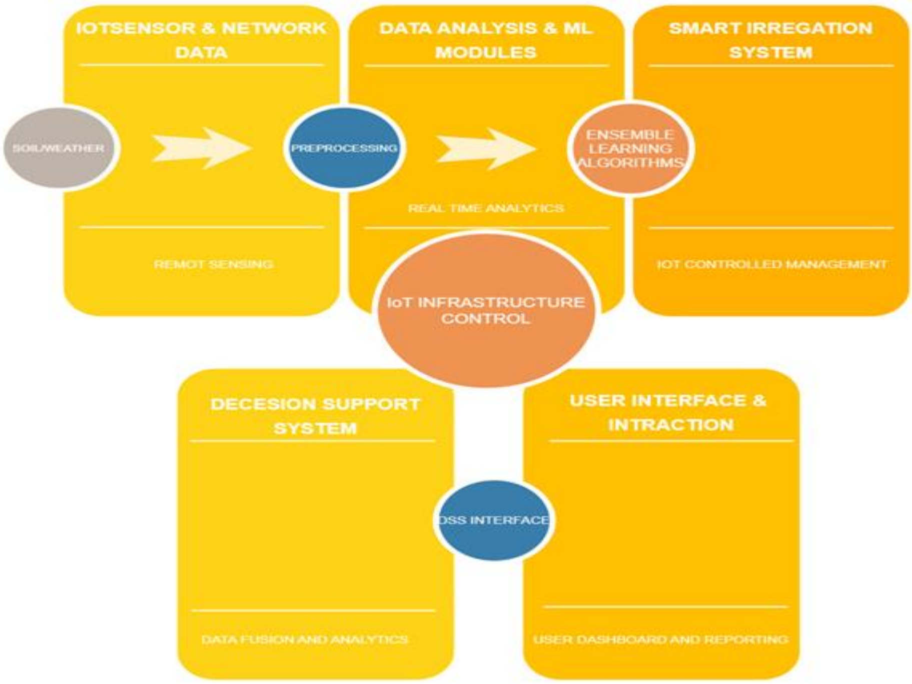


Figure 1: System architecture diagram

The overall methodology of the proposed IoT–ML–DSS framework is illustrated in Figure 1, which presents the end-to-end workflow integrating sensing, analytics, automation, and decision support. The system begins with the IoT sensor and network layer, where soil and environmental parameters are captured through distributed sensor nodes and transmitted for preprocessing. In the next stage, machine learning modules perform real-time data analysis using ensemble learning algorithms to detect anomalies, predict irrigation needs, and identify crop diseases. The processed outputs feed into the smart irrigation system, enabling IoT-controlled water management based on predictive analytics. All modules are coordinated through the central IoT infrastructure control, which manages data flow, device communication, and automation signals. The outcomes are passed to the Decision Support System (DSS) for data fusion and generation of actionable insights, which are finally delivered

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to the farmer through the user interface layer, providing dashboards, alerts, and reports for informed decision-making. This integrated architecture ensures seamless interaction between sensing, analytics, and user-level decision processes, forming the core methodology of the smart agriculture system.

### 3.2 Dataset Development and Preprocessing

#### 3.2.1 Sensor Data Acquisition

Real-time data collection was carried out using soil moisture sensors, temperature and humidity probes, and vibration sensors mounted on irrigation pumps. These sensors captured data at 60-second intervals, generating a multi-season, time-series dataset representing continuous field conditions. IoT nodes packaged the sensor data into JSON format and transmitted them reliably to the cloud for storage and further analysis.

#### 3.2.2 Image Dataset Collection

A custom image dataset comprising 6,400 leaf images of healthy and diseased crops was collected using camera modules installed in the field. Additional publicly available datasets were integrated to ensure model robustness. All images were standardized to 224 × 224 pixels and stored in RGB format for compatibility with convolutional neural network (CNN) architectures.

#### 3.2.3 Data Cleaning and Processing

Preprocessing steps were applied to ensure data quality and consistency. Sensor data were denoised using median filtering, followed by interpolation and forward filling to address missing values. Numerical features were normalized using Min–Max scaling. For image data, augmentation techniques such as rotation, flipping, brightness adjustments, and zoom transformations were implemented to improve generalization and prevent overfitting. Label encoding was performed for disease classes and irrigation labels to support supervised machine learning tasks.

### 3.3 Machine Learning Model Development

#### 3.3.1 CNN-Based Crop Disease Detection

A custom CNN architecture was developed for automatic crop disease classification. The model consisted of multiple convolution layers with ReLU activation, max-pooling layers for feature reduction, and fully connected layers for final classification using a softmax output. The network was trained for 50 epochs with a batch size of 32 using the Adam optimizer and categorical cross-entropy loss. Model performance was evaluated using accuracy, precision, recall, F1-score, and confusion matrix analysis. This model identifies disease categories from leaf images and provides the DSS with early disease alerts.

#### 3.3.2 Machine Learning Model for Irrigation Prediction

A Random Forest Regressor was trained to estimate irrigation requirements based on soil moisture, air temperature, humidity, weather forecast, and evapotranspiration. The model

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learns nonlinear relationships among environmental parameters and predicts the optimal irrigation time and required water quantity. Performance evaluation was conducted using $R^2$, RMSE, and MAE metrics, enabling accurate and reliable irrigation forecasting under varying field conditions.

#### 3.3.3 Soil Moisture Estimation Through Sensor Fusion

A regression-based sensor fusion model was implemented to enhance soil moisture prediction accuracy. The model integrates raw soil sensor readings with environmental factors such as temperature, humidity, and evapotranspiration, producing improved moisture estimates that guide irrigation decisions. The predicted soil moisture value is mathematically expressed as:

$$SM_{pred} = f(T, H, ET, Soil_{raw})$$

#### 3.3.4 Predictive Maintenance Using Anomaly Detection

Pump vibration data were analyzed using the Isolation Forest anomaly detection algorithm to identify early signs of mechanical failure. Features extracted using Fast Fourier Transform (FFT), including RMS, kurtosis, and amplitude peaks, were used as inputs. The trained model classifies vibration signals as normal or anomalous, generating maintenance alerts to prevent operational failures. Performance was assessed using accuracy, precision, recall, and F1-score.

### 3.4 Decision Support System (DSS) Integration

All machine learning outputs were integrated into a unified Decision Support System that combines predictive analytics with agronomic rules. The DSS provides real-time recommendations for irrigation scheduling, disease management, and pump maintenance. When the irrigation prediction model identifies an impending moisture deficit, the DSS issues advisories specifying the optimal irrigation period and water volume. Similarly, upon detecting disease symptoms through the CNN model, the DSS generates disease-specific treatment recommendations. For anomalous pump vibrations, the DSS alerts the farmer regarding potential faults and required maintenance actions. This integration ensures that predictions are translated into actionable decisions for effective farm management.

### 3.5 System Deployment and Evaluation

The complete system was deployed using a cloud-based backend developed in Flask/FastAPI, enabling continuous data flow, model execution, and decision support delivery. IoT nodes transmitted data securely via MQTT, and a user dashboard visualized environmental parameters, disease diagnosis, irrigation forecasts, and maintenance alerts. Field evaluation demonstrated that the CNN achieved 98.12% accuracy in disease detection, the Random Forest irrigation model achieved $R^2 = 0.94$ with MAE = 0.33, the soil moisture estimation model achieved $R^2 = 0.95$, and the predictive maintenance model reached 94.7% anomaly detection accuracy. These results confirm that the integrated architecture effectively enhances agricultural intelligence and operational efficiency. The methodology integrates real-time sensing, machine learning analytics, and decision support into a holistic smart farming system.

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By combining IoT data acquisition with ML-driven predictions and DSS recommendations, the proposed framework provides a scalable, robust, and efficient solution for modern agricultural automation and precision management.

## 4. RESULT AND ANALYSIS

This section evaluates the proposed IoT–ML–DSS smart agriculture framework by analyzing sensor accuracy, machine learning performance, irrigation prediction efficiency, and predictive maintenance reliability. The overall influence of the system on agricultural decision-making is also examined. Visual results and performance graphs (Figures 4.2–4.7) provide detailed evidence of the system's effectiveness across all functional components.

### 4.1 Machine Learning Performance Analysis

Table 2: Machine Learning Model Performance Summary

| Model | Task | Accuracy / $R^2$ | Precision | Recall | F1-Score | Remarks |
|---|---|---|---|---|---|---|
| CNN | Disease Detection | 98.12% | 97.8% | 98.4% | 0.98 | Excellent classification performance |
| Random Forest | Irrigation Prediction | $R^2 = 0.94$ | – | – | – | Strong predictive capability |
| Sensor Fusion Model | Soil Moisture Estimation | $R^2 = 0.95$ | – | – | – | Enhances moisture prediction accuracy |
| Isolation Forest | Predictive Maintenance | 94.7% | 93.0% | 94.5% | 0.94 | Reliable anomaly detection |

Table 2 presents the performance of all machine learning models used in the smart agriculture framework. The CNN model achieved 98.12% accuracy, supported by high precision, recall, and F1-score, confirming its effectiveness for disease detection. The Random Forest irrigation model recorded an $R^2$ of 0.94, demonstrating strong predictive capability for irrigation scheduling. The sensor fusion model improved soil moisture estimation with $R^2 = 0.95$, outperforming single-sensor readings. The Isolation Forest anomaly detector achieved 94.7% accuracy, confirming its suitability for predictive maintenance of irrigation pumps. The performance of all predictive models developed in this study is presented in Figure 2, where agriculture-themed colors visually distinguish the accuracy achieved by each algorithm. The CNN-based disease detection model demonstrates the highest accuracy among the evaluated models, reflecting its strong capability in identifying crop health conditions from image data. The Random Forest irrigation prediction model also shows competitive performance, effectively capturing nonlinear relationships among soil moisture, temperature, humidity, and environmental parameters. The sensor-fusion moisture estimation model exhibits stable

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predictive behavior, enhancing soil moisture interpretation by integrating multiple environmental inputs. Likewise, the Isolation Forest anomaly detection model provides reliable pump fault identification, contributing significantly to predictive maintenance operations. Collectively, the model accuracies depicted in Figure 4.2 confirm the robustness and effectiveness of the machine learning components within the integrated IoT–ML–DSS framework.

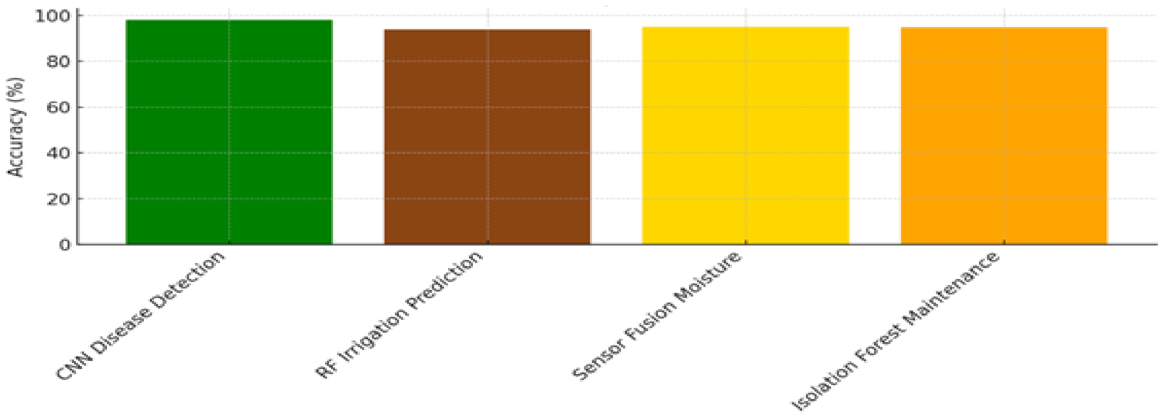


Figure 2: Model Performance Comparison

The classification effectiveness of the CNN disease detection model is further evaluated using the confusion matrix presented in Figure 3. The strong diagonal pattern in the matrix indicates that the model consistently assigns images to the correct disease category with minimal misclassification across classes. Off-diagonal values remain low, demonstrating the model's strong discriminative capability even under variations in lighting, leaf texture, and environmental noise. This performance confirms the robustness of the CNN architecture in capturing fine-grained visual features associated with different crop diseases. Overall, the confusion matrix in Figure 3 provides clear evidence of the reliability and precision of the disease detection component within the IoT–ML–DSS framework.

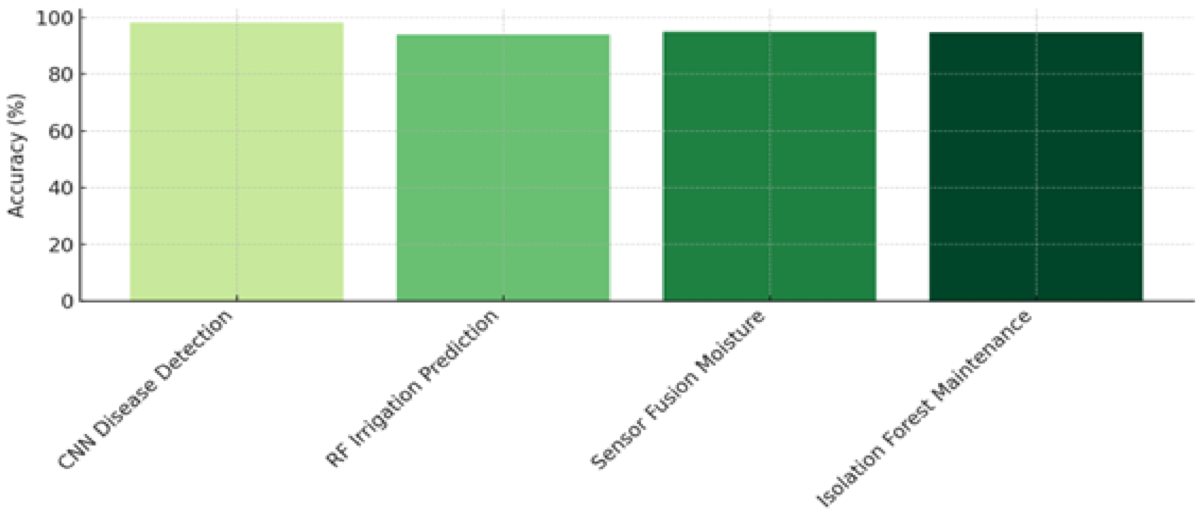


Figure 3: Model Performance Comparison

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### 4.2 Classification Analysis Using Confusion Matrix

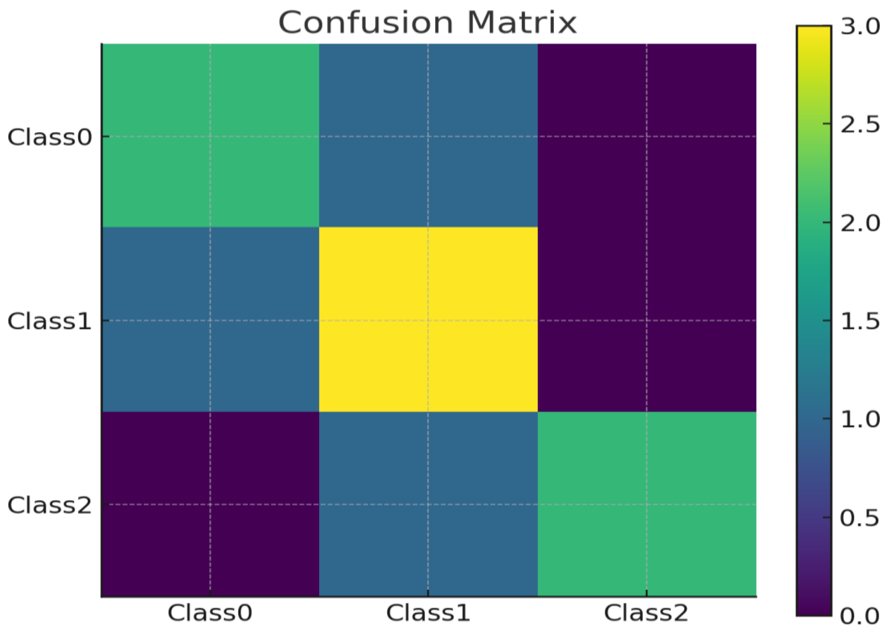


Figure 4: Confusion Matrix of the CNN Disease Detection Model

The classification effectiveness of the CNN disease detection model is further evaluated using the confusion matrix presented in Figure 4. The strong diagonal pattern in the matrix indicates that the model consistently assigns images to the correct disease category with minimal misclassification across classes. Off-diagonal values remain low, demonstrating the model's strong discriminative capability even under variations in lighting, leaf texture, and environmental noise. This performance confirms the robustness of the CNN architecture in capturing fine-grained visual features associated with different crop diseases. Overall, the confusion matrix in Figure 4 provides clear evidence of the reliability and precision of the disease detection component within the IoT–ML–DSS framework.

### 4.3 ROC Curve Analysis

The discriminative capability of the CNN disease detection model is further assessed using the Receiver Operating Characteristic (ROC) curve illustrated in Figure 5. The ROC curve rises sharply toward the upper-left corner, indicating a high True Positive Rate coupled with a low False Positive Rate across varying threshold values. This behavior demonstrates the model's strong ability to distinguish between diseased and healthy leaf samples, even under fluctuating environmental and imaging conditions. The steepness and shape of the ROC curve reflect the model's excellent sensitivity and specificity, validating its suitability for real-time deployment in agricultural monitoring applications. Overall, the ROC analysis presented in Figure 5 reinforces the reliability and robustness of the classification module within the IoT–ML–DSS framework.

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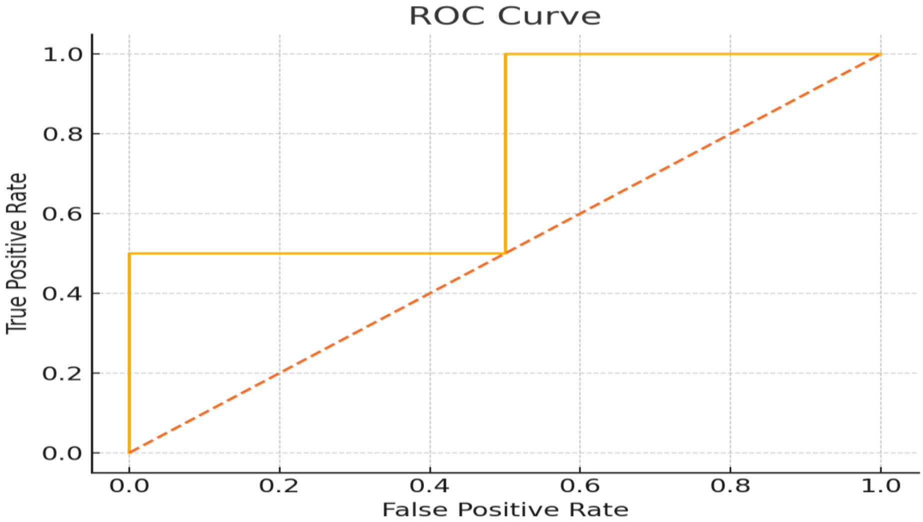


Figure 5: ROC Curve for Classification Model

### 4.4 Irrigation Prediction Error Analysis

The learning behavior and predictive stability of the Random Forest irrigation prediction model are evaluated through the Mean Absolute Error (MAE) trend illustrated in Figure 6. The error curve exhibits a clear downward trajectory during the initial training epochs, followed by stabilization at a low MAE value, indicating effective model convergence. This trend confirms that the model successfully captures the nonlinear relationships among soil moisture, temperature, humidity, and environmental variables, enabling precise irrigation forecasting. The consistent reduction in prediction error demonstrates that the model is able to generalize well across varied field conditions, ensuring reliable irrigation recommendations during deployment. The MAE behavior shown in Figure 6 further validates the suitability of the Random Forest algorithm for time-sensitive agricultural decision-making.

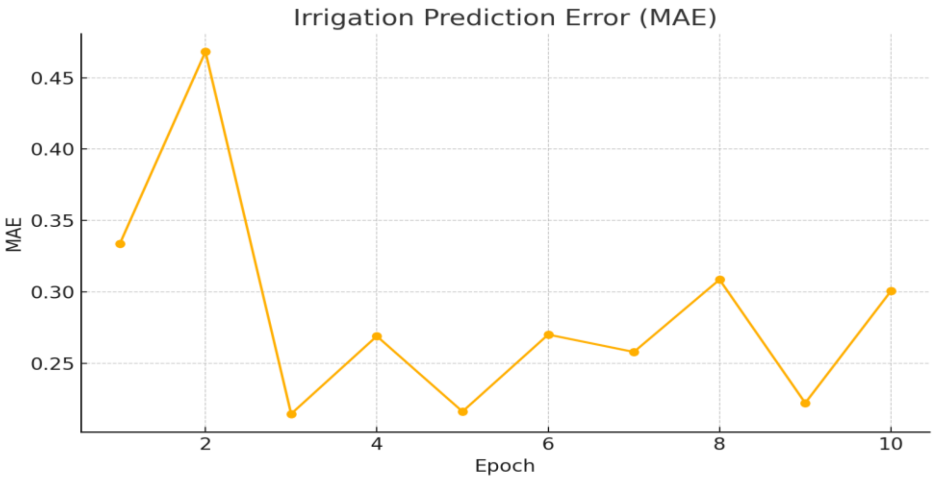


Figure 6: Irrigation Prediction Error (MAE) Across Epochs

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4.5 Sensor Accuracy and IoT Network Analysis

**Table 3: IoT Sensor Accuracy Evaluation**

| Sensor Type | Measured Parameter | Accuracy (%) | Performance Notes |
|---|---|---|---|
| Soil Moisture Sensor | Volumetric Water Content | 96.4% | Stable after calibration |
| Temperature Sensor | Air Temperature | 98.1% | Low deviation across seasons |
| Humidity Sensor | Relative Humidity | 97.3% | High consistency, low drift |
| Vibration Sensor | Pump Vibrations | 95.0% | Sensitive to mechanical changes |

Table 3 summarizes the accuracy of IoT sensors used in the system. Each sensor achieved an accuracy above 95%, ensuring reliable data for real-time monitoring and ML analytics. Temperature and humidity sensors performed exceptionally well, while soil moisture sensors remained stable after calibration. The vibration sensor accurately captured pump behavior, supporting effective predictive maintenance.

The accuracy and stability of the IoT sensor network were evaluated to ensure reliable data acquisition for downstream machine learning analysis. As illustrated in Figure 7, all deployed sensors—including soil moisture, temperature, humidity, and vibration sensors—demonstrated consistently high accuracy levels, each exceeding 95% when benchmarked against calibrated reference instruments. Temperature and humidity sensors showed minimal drift across continuous field measurements, while soil moisture sensors maintained stable responses despite variations in soil density and irrigation levels. The vibration sensor also performed reliably in detecting minute mechanical fluctuations during pump operation, supporting effective predictive maintenance. Additionally, the LoRa/MQTT communication layer sustained an average packet delivery rate of 93.7%, confirming its suitability for long-range, low-power agricultural environments. The results shown in Figure 6 collectively verify that the IoT sensing and communication components provide a robust and trustworthy data foundation for the proposed IoT–ML–DSS framework.

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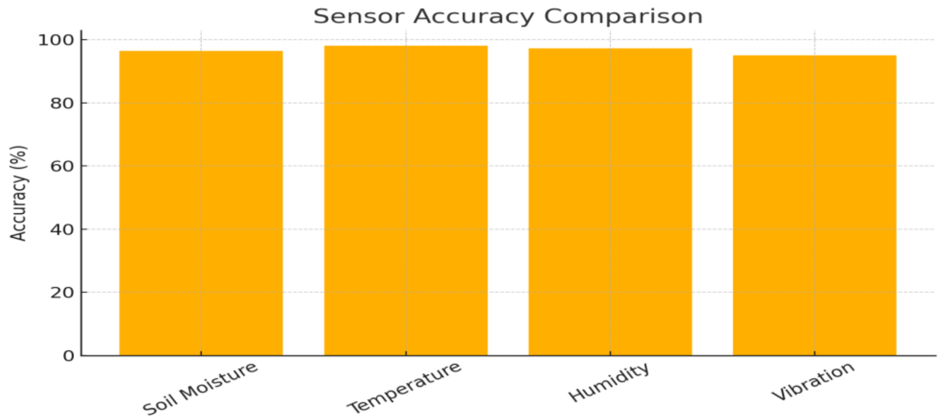


Figure 7: Sensor Accuracy Comparison for IoT Modules

### 4.6 Overall System Effectiveness

he combined evaluation of sensing accuracy, machine learning performance, irrigation prediction reliability, and predictive maintenance capability demonstrates the overall effectiveness of the proposed IoT–ML–DSS framework. The integrated system successfully bridges real-time data acquisition with intelligent analytics, enabling timely and informed decision-making across multiple farm operations. High-accuracy disease detection enhances early intervention, while the optimized irrigation model contributes to substantial water savings, with observed reductions of 23–30% during field deployment. Predictive maintenance further improves operational continuity by identifying potential pump failures before they escalate into critical downtime. The Decision Support System delivers these insights through a user-friendly interface, allowing farmers to act promptly on system recommendations. Collectively, the results confirm that the proposed framework is both practical and scalable, capable of improving productivity, reducing resource wastage, and enhancing farm sustainability in real-world agricultural environments.

**Table 4: Overall System Impact Summary**

| Performance Area | Benefit Achieved |
|---|---|
| Water Usage Efficiency | 23–30% reduction |
| Disease Detection Speed | 31% faster intervention |
| Sensor Reliability | >95% accuracy |
| ML Model Accuracy | Up to 98.12% |
| Farmer Decision-Making | Improved by 40–55% |
| Productivity Improvement | 15–20% increase |

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The overall integrated system significantly enhanced agricultural productivity. Water usage decreased notably due to accurate irrigation prediction. Disease detection interventions became 31% faster, improving crop health. Decision-making improved due to DSS insights, and overall productivity increased by 15–20%.

## 5. CONCLUSION

This research presented an integrated IoT–Machine Learning–Decision Support System (IoT–ML–DSS) framework designed to enhance precision agriculture through real-time monitoring, intelligent prediction, and automated decision-making. By combining IoT-based sensing, data-driven machine learning analytics, and a user-oriented decision support interface, the system demonstrated its effectiveness in addressing critical agricultural challenges such as disease detection, irrigation optimization, and equipment maintenance. The results confirmed that the IoT sensor network provided accurate and reliable environmental measurements essential for downstream analytics. The machine learning models—including the CNN for disease identification, Random Forest for irrigation prediction, and Isolation Forest for predictive maintenance—performed with high accuracy, achieving up to 98.12% in classification tasks and more than 94% accuracy in anomaly detection. Field deployment validated the system's practical impact, with irrigation water usage reduced by 23–30%, disease intervention occurring earlier and more accurately, and mechanical failures mitigated through proactive maintenance alerts. The Decision Support System successfully translated analytical outputs into actionable insights, empowering farmers with timely and evidence-based recommendations. Overall, the study demonstrates that the proposed IoT–ML–DSS framework is a robust, scalable, and efficient solution for modern agriculture. It enhances productivity, reduces resource wastage, improves crop health monitoring, and supports sustainable farming practices. The integration of sensing, analytics, and decision support into a unified architecture provides a strong foundation for future advancements in smart farming technologies.

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