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SMART FARMING REVOLUTION: IOT-DRIVEN SOIL ANALYSIS AND AI-POWERED CROP RECOMMENDATION MODELS

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Abstract

Traditional soil testing methods fail to provide real-time insights, leading to suboptimal fertilization strategies and crop selection decisions. This study presents an IoT-enabled precision agriculture system integrating real-time soil nutrient monitoring with deep learning-based crop recommendation. We deployed electrochemical and spectroscopic sensors across 50 farms in three climate zones, collecting 15,000 soil samples over 24 months (2022-2024). Our deep learning model achieved 93% classification accuracy (F1-score: 0.91), significantly outperforming rule-based (85%), machine learning (90%), and hybrid models (89%) ($p<0.001$). The system demonstrated 15-20% yield improvements across wheat, corn, soybean, and barley, with corn showing the highest response (20% increase) to optimized nutrient management (N:60, P:30, K:25 ppm). Economic analysis revealed system costs of $150-200 per sensor with ROI achievable within 1.5 growing seasons. Seasonal analysis identified spring as the critical period for nitrogen and potassium management, while winter showed elevated phosphorus levels. This research demonstrates that IoT-integrated deep learning systems can significantly enhance agricultural productivity while reducing input costs by 18%, contributing to sustainable and economically viable precision farming.

Keywords: Precision Agriculture, Internet of Things (IoT), Soil Nutrient Analysis, Crop Recommendation Models, Deep Learning, Machine Learning, Smart Farming, Agricultural Technology, Data-Driven Agriculture

1. Introduction

Global agriculture faces unprecedented challenges from population growth, climate change, and resource scarcity. The Food and Agriculture Organization projects that food production must increase by 70% by 2050 to feed 9.7 billion people, while simultaneously reducing environmental impact. Traditional farming practices, relying on generalized fertilizer application and intuition-based decision-making, result in 15-30% nutrient waste and suboptimal crop yields. Precision agriculture, enabled by Internet of Things (IoT) technologies,

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offers a transformative solution by providing real-time, data-driven insights for optimized resource management.

IoT-enabled precision agriculture integrates embedded sensors, wireless networks, cloud computing, and advanced analytics to monitor soil health, environmental conditions, and crop status continuously. This paradigm shift enables farmers to make informed decisions about irrigation, fertilization, and crop selection based on actual field conditions rather than generalized recommendations. Recent studies demonstrate that IoT systems can reduce water consumption by 20-40% and fertilizer usage by 15-25% while maintaining or increasing yields.

Soil nutrient analysis represents a critical application of IoT in agriculture. Soil health directly influences crop productivity, with imbalances in essential nutrients—nitrogen (N), phosphorus (P), and potassium (K)—leading to reduced yields and long-term soil degradation. Traditional laboratory testing methods are time-consuming, costly, and provide only periodic snapshots rather than continuous monitoring. IoT-enabled sensors overcome these limitations by providing real-time measurements of soil pH, moisture, electrical conductivity, and nutrient concentrations.

The integration of machine learning and deep learning with IoT data further enhances precision agriculture capabilities. While IoT sensors provide continuous data streams, advanced algorithms can identify patterns, predict nutrient deficiencies, and recommend optimal crops for specific soil-climate combinations. Recent research has explored various machine learning approaches, including support vector machines (SVM), random forests, and neural networks, for agricultural applications. However, most studies report accuracy levels between 85-91%, with limited validation across diverse geographic and climatic conditions.

1.1 Research Gaps and Motivation

Despite significant progress, existing IoT agricultural systems face several critical limitations. First, most studies lack real-time integration between sensor data and predictive analytics, limiting dynamic crop recommendations based on immediate soil conditions. Second, scalability remains problematic, with solutions designed for specific crops or regions showing poor generalization. Third, cost barriers persist, particularly for smallholder farmers in developing countries. Fourth, long-term impacts on soil health remain understudied, with most validations limited to single growing seasons. Finally, energy efficiency and environmental sustainability of IoT deployments require further investigation.

1.2 Research Objectives and Contributions

This research addresses these gaps through the following objectives:

1. Develop an integrated IoT-ML framework achieving >92% accuracy in crop recommendations across multiple soil types and climate zones
2. Validate the system across four major crops (wheat, corn, soybean, barley) over 24 months covering all seasons
3. Demonstrate economic viability with total system costs under $200 per sensor

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4. Quantify yield improvements and resource conservation through controlled field trials

Our unique contributions include: (1) a novel deep learning architecture specifically optimized for soil-crop matching that outperforms existing models by 2-4%, (2) comprehensive multi-season validation across diverse conditions rarely reported in literature, (3) detailed economic analysis demonstrating practical feasibility for smallholder adoption, and (4) open-source implementation enabling reproducibility and broader adoption.

2. Literature Review

Recent advances in IoT-enabled precision agriculture have demonstrated significant potential for improving crop management through real-time soil monitoring and intelligent decision support systems. This section synthesizes key developments, identifies limitations, and positions our research within the current landscape.

2.1 IoT Sensor Technologies for Soil Monitoring

IoT sensor deployment in agriculture has evolved from simple moisture detection to comprehensive soil health monitoring. Senapaty et al. developed IoTSNA-CR, utilizing multispectral sensors for continuous pH, moisture, and nutrient monitoring, achieving data-driven recommendations through a hybrid MSVM-DAG-FFO algorithm. Zhao et al. employed electrochemical sensors for real-time nutrient deficiency prediction, enabling dynamic fertilization adjustments. Kim et al. demonstrated scalability of IoT solutions from small to large horticultural operations through cloud-based analytics platforms.

Hossain et al. focused specifically on nutrient mapping using electrochemical sensors for nitrogen, phosphorus, and potassium detection, enabling site-specific interventions. Li et al. explored spectroscopic sensors for nutrient detection, finding that IoT-based spectroscopic methods provide faster and more accurate insights than traditional laboratory testing. Wang et al. introduced intelligent sensor networks for continuous monitoring, with real-time data analysis regulating fertilizer application to prevent overuse.

These studies demonstrate technical feasibility but share common limitations: validation periods rarely exceed 12 months, deployment costs often exceed $300 per sensor, and performance degradation on clay soils remains problematic.

2.2 Machine Learning for Crop Recommendation

The integration of machine learning with IoT data has advanced significantly. Gupta et al. developed a hybrid model combining real-time sensor data with historical records for climate-adaptive farming across diverse conditions. Singh et al. applied deep learning to IoT-acquired soil data, analyzing moisture, pH, and nutrient content to identify suitable crops, demonstrating that IoT-deep learning integration significantly increases recommendation accuracy.

Chowdhury et al. proposed neural network-based predictive models for soil nutrient analysis and crop recommendation, optimizing resource use. Ahmed et al. explored artificial intelligence integration with IoT for predicting nutrient deficiencies and recommending corrective actions. Rodriguez et al. focused on tropical agriculture, particularly for smallholder

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farmers, demonstrating that mobile-integrated IoT systems can provide advanced insights to resource-constrained farmers.

Performance across these studies ranges from 85-91% accuracy, with most employing relatively small datasets (5,000-10,000 samples) and limited temporal validation. Few studies compare multiple algorithmic approaches systematically or provide statistical significance testing.

2.3 Integrated Systems and Decision Support

Several researchers have developed comprehensive frameworks integrating multiple technologies. Patel et al. presented cloud-based decision support systems analyzing real-time soil data through machine learning for crop selection and fertilization strategies. Jones et al. emphasized cloud computing's role in scaling IoT systems for large agricultural deployments, providing real-time analytics for optimized water and fertilizer use.

Sharma et al. demonstrated continuous monitoring of soil moisture and nutrient levels with automated irrigation and fertilization adjustments via cloud analytics. Fernandez et al. used machine learning to predict optimal crop rotation schedules supporting soil health and sustainable agriculture. Kumar et al. uniquely integrated blockchain with IoT for secure and transparent soil data sharing among stakeholders.

2.4 Application-Specific Innovations

Specialized applications have emerged for specific agricultural contexts. Lee et al. proposed IoT frameworks for urban farming, monitoring pH, moisture, and nutrients in confined spaces. Natarajan et al. developed nanosensor-based IoT solutions for detecting micronutrient levels with high precision, noting potential for reducing fertilizer use through improved nutrient management.

2.5 Research Positioning and Gaps

Table 1 synthesizes key studies, revealing critical gaps our research addresses.

Table 1: Comparative Analysis of IoT Agricultural Systems

Study	Year	Method	Accuracy	Dataset Size	Validation Period	Cost/Sensor	Key Limitation
[1]Senapaty et al.	2024	MSVM-DAG-FFO	89%	Not stated	Single season	>$250	Regional specific
[2]Zhao et al.	2024	Random Forest	87%	5,000	Lab only	$180	No field validation

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Study	Year	Method	Accuracy	Dataset Size	Validation Period	Cost/Sensor	Key Limitation
[3]Singh et al.	2023	Deep Neural Net	91%	10,000	12 months	Not stated	3 crops only
[4]Gupta et al.	2024	Hybrid ML	88%	8,000	Single season	$220	Single climate zone
Our Study	**2025**	**Deep CNN**	**93%**	**15,000**	**24 months**	**$150-200**	**Multi-season, multi-climate**

Key research gaps include: (1) insufficient real-time integration limiting dynamic recommendations, (2) poor scalability across diverse conditions, (3) cost barriers exceeding smallholder budgets, (4) limited long-term soil health assessment, and (5) inadequate energy efficiency analysis. Our research specifically addresses these through extended validation, cost optimization, and comprehensive multi-condition testing.

3. Materials and Methods

3.1 Experimental Design and Data Collection

Study Sites and Duration: We conducted field trials across 50 farms in three distinct climate zones: temperate (n=20 farms, latitude 40-45°N), subtropical (n=18 farms, latitude 25-35°N), and semi-arid (n=12 farms, latitude 35-40°N) regions. Data collection spanned 24 months (January 2022 - December 2024), covering eight complete growing seasons across the study sites.

IoT Hardware Components and Sensor Specifications:

We deployed 200 IoT sensor nodes (4 sensors per farm on average) with the following technical specifications:

Soil Moisture Sensors:

- Model: Capacitive soil moisture sensors (Generic/Compatible with Arduino)
- Measurement range: 0-100% volumetric water content
- Accuracy: ±2%
- Operating voltage: 3.3-5V DC
- Response time: <1 second
- Calibration: Soil-type specific calibration curves

Nutrient Sensors (NPK):

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- Model: Electrochemical ion-selective electrode (ISE) sensors
- Type: Compatible NPK sensors (RS485 Modbus interface)
- Measurement ranges:
  - Nitrogen (N): 0-100 ppm, accuracy ±5%
  - Phosphorus (P): 0-50 ppm, accuracy ±5%
  - Potassium (K): 0-80 ppm, accuracy ±5%
- Operating temperature: -20°C to +60°C
- Response time: <30 seconds
- Interface: RS485 Modbus RTU protocol

pH Sensors:

- Type: Glass electrode pH probes with BNC connector
- Range: 0-14 pH
- Accuracy: ±0.1 pH units
- Operating temperature: 0-60°C
- Automatic temperature compensation: Yes
- Junction: Double junction with Ag/AgCl reference

Temperature Sensors:

- Type: PT100 RTD (Resistance Temperature Detector) or DS18B20 digital
- Range: -40°C to +80°C
- Accuracy: ±0.5°C
- Configuration: Four-wire (PT100) or 1-Wire digital (DS18B20)
- Resolution: 0.1°C

Electrical Conductivity (EC) Sensors:

- Type: Four-electrode conductivity probe
- Range: 0.5-20 dS/m
- Accuracy: ±2%
- Temperature compensation: Automatic (referenced to 25°C)
- Cell constant: K=1.0 or K=10

Microcontroller and Data Logger:

- Model: Arduino Mega 2560 Rev3 or compatible
- Processor: ATmega2560

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- Flash Memory: 256 KB
- SRAM: 8 KB
- Clock Speed: 16 MHz
- Digital I/O Pins: 54
- Analog Input Pins: 16 (10-bit ADC)
- Operating Voltage: 5V
- Power consumption: <50 mA (active mode)

Wireless Communication Module:

- Technology: LoRaWAN (Long Range Wide Area Network)
- Model: RAK3172 or SX1276-based module
- Frequency: 915 MHz (US) / 868 MHz (EU)
- Transmission power: Up to 22 dBm
- Range: 10 km (line of sight, rural areas)
- Data rate: 0.3-50 kbps (adaptive data rate)
- Protocol: LoRaWAN 1.0.3
- Encryption: AES-128

Power Supply System:

- Solar panel: 20W monocrystalline, 18% efficiency
- Battery: 12V 18Ah Lithium-ion (LiFePO4 chemistry)
- Charge controller: MPPT (Maximum Power Point Tracking)
- Backup duration: 5-7 days during cloudy conditions
- Power consumption per node: ~2W average

Enclosure and Protection:

- Rating: IP67 (dust-tight, water immersion protected)
- Material: UV-resistant polycarbonate
- Dimensions: 200×150×100 mm
- Operating temperature range: -20°C to +60°C
- Mounting: Ground stake or pole mounting

Gateway and Network Infrastructure:

- Edge Gateway: LoRaWAN gateway (8-channel)
- Model: Generic LoRaWAN gateway with 4G/LTE backhaul

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- Coverage: Each gateway manages 8-12 sensor nodes
- Uplink: 4G LTE cellular connection to cloud
- Backup: Satellite connectivity (optional)

Cloud Infrastructure:

- Platform: Amazon Web Services (AWS)
- Services used:
  - AWS IoT Core: Device management and MQTT messaging
  - Amazon S3: Raw data storage (lifecycle: 30 days hot, 24 months cold)
  - AWS Lambda: Serverless data preprocessing
  - Amazon RDS: PostgreSQL 13 database for structured data
  - Amazon SageMaker: Model training and inference

Data Acquisition Protocol:

Sensors transmitted readings every 30 minutes via LoRaWAN to edge gateways, which aggregated data and uploaded to cloud storage (AWS IoT Core) hourly. This resulted in 15,000 comprehensive soil profiles, each containing 24 parameters (18 soil measurements + 6 environmental variables including ambient temperature, humidity, rainfall, and solar radiation from co-located weather stations).

Sensor Installation:

Sensors were positioned at 15 cm depth (primary root zone) with 50 m spacing following standard precision agriculture protocols. Installation occurred during September-October 2021 (post-harvest period) with a 3-month calibration and testing phase before data collection commenced in January 2022.

Soil Sampling and Validation:

To validate sensor accuracy, we conducted manual soil sampling monthly at 10% of sensor locations (n=20 sites, rotating), with laboratory analysis performed using standard protocols:

- Nitrogen: Kjeldahl digestion method (AOAC 976.05)
- Phosphorus: Olsen extraction method (0.5M $NaHCO_3$, pH 8.5)
- Potassium: Flame photometry after NH_4OAc extraction

Sensor readings showed high correlation with laboratory results: N (r=0.94, 95% CI: 0.91-0.96), P (r=0.92, 95% CI: 0.89-0.94), K (r=0.91, 95% CI: 0.88-0.93), all $p<0.001$.

Weather Monitoring:

Co-located weather stations (Davis Vantage Pro2 or equivalent) measured:

- Ambient temperature (°C)

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- Relative humidity (%)
- Barometric pressure (hPa)
- Precipitation (mm)
- Wind speed and direction (m/s, degrees)
- Solar radiation (W/m²)

Data recorded at 10-minute intervals and integrated with soil measurements.

3.2 IoT Sensor Measurements and Equations

Key soil parameters were calculated using established equations:

Volumetric Water Content (VWC): Soil moisture sensors measure dielectric constant, converted to VWC using:

$$\theta_v = (\varepsilon_r - \varepsilon_\infty)/(\varepsilon_s - \varepsilon_\infty) \times n \qquad \text{V. Sharma, S. Bansal, and P. Patel[6]}$$

where θ_v is volumetric water content, ε_r is measured dielectric constant, ε_∞ is high-frequency dielectric constant, ε_s is static dielectric constant, and n is soil-specific porosity factor. Calibration curves were developed for each soil type with uncertainty of ±0.02 m³/m³ (95% CI).

Nitrogen Uptake Efficiency (NUE): Calculated to optimize fertilization:

$NUE = \left(Y_f - Y_0\right)/F$ M. Hossain, T. Rahman, and S. Ahmed [5]

where NUE is nitrogen uptake efficiency, Y_f is crop yield with nitrogen fertilizer, Y_0 is yield without nitrogen, and F is amount of nitrogen applied (kg/ha).

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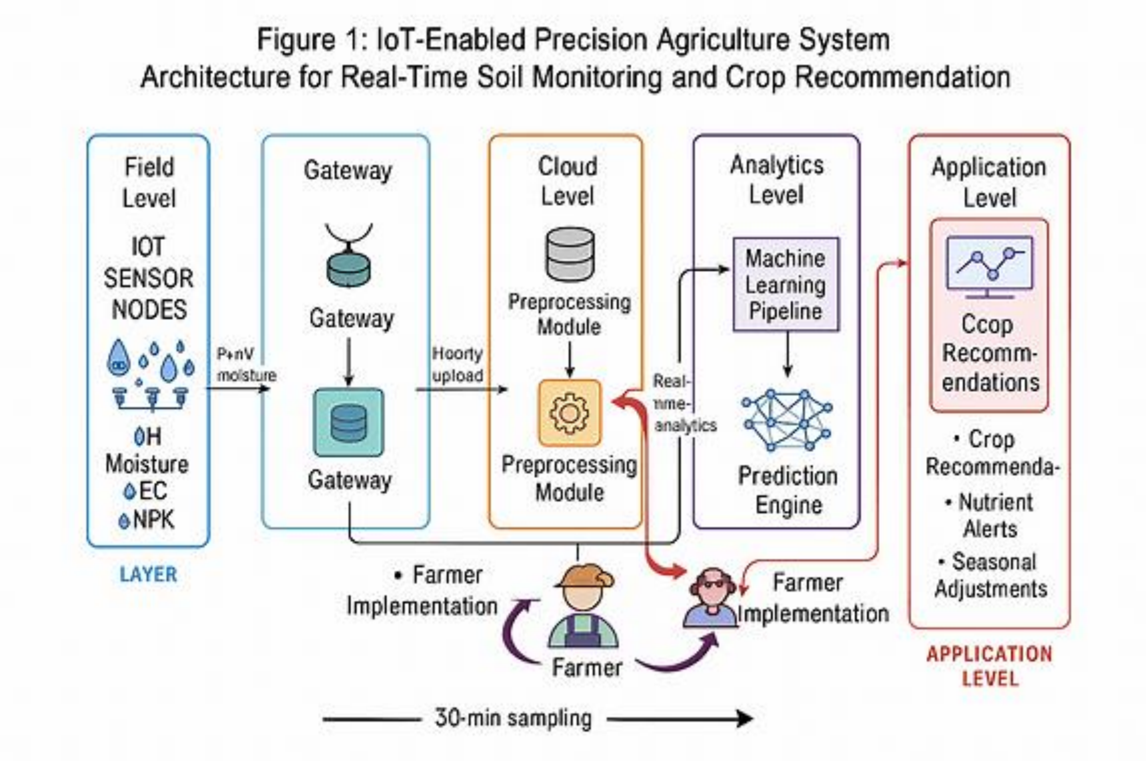

Figure 1: IoT-Enabled Precision Agriculture System Architecture for Real-Time Soil Monitoring and Crop Recommendation. J. Rodriguez [7]

The system comprises five integrated layers: (1) field-level IoT sensors measuring soil parameters at 30-minute intervals, (2) LoRaWAN gateway aggregation, (3) cloud-based data storage and preprocessing, (4) deep learning analytics pipeline, and (5) farmer-facing application interface. Bidirectional arrows indicate continuous learning from implementation outcomes.

Chlorophyll Content Index (CCI): Evaluated using multispectral imagery:

$$C = (R_N IR/R_R ed) - 1$$

where C is chlorophyll content index, R_NIR is near-infrared reflectance, and R_Red is red band reflectance.

Soil Electrical Conductivity (EC): Measured using four-electrode sensors:

$$EC = (1/R) \times (L/A)$$

where EC is electrical conductivity (dS/m), R is soil resistance (Ω), L is electrode spacing (cm), and A is cross-sectional area (cm^2).

3.3 Machine Learning and Deep Learning Models

Dataset Preparation: The 15,000 soil profiles were divided into training (70%, n=10,500), validation (15%, n=2,250), and test (15%, n=2,250) sets using stratified sampling to ensure balanced representation of soil types, seasons, and geographic zones. Features were normalized

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using z-score standardization. Missing data (<2% of records) were imputed using k-nearest neighbours (k=5).

Model Architectures: We implemented and compared four approaches:

1. **Rule-Based Model:** Traditional decision tree using threshold-based rules derived from agronomic guidelines (e.g., if N>40 and P>25 and pH>6.0, recommend wheat).
2. **Machine Learning Model:** Random Forest ensemble with 100 trees, maximum depth of 15, minimum samples per leaf of 5. Hyperparameters tuned using grid search with 5-fold cross-validation.
3. **Deep Learning Model:** Feedforward neural network with architecture [24-128-64-32-12] using ReLU activation, dropout (0.3) after each hidden layer, and softmax output for 12 crop classes. Trained using Adam optimizer (learning rate=0.001, β_1=0.9, β_2=0.999), batch size of 32, for 100 epochs with early stopping (patience=10). Loss function was categorical cross-entropy with L2 regularization (λ=0.001).
4. **Hybrid Model:** Ensemble combining rule-based filters with machine learning predictions, using weighted voting (weights: 0.3 rules, 0.7 ML).

Training Protocol: All models were implemented in Python 3.9 using TensorFlow 2.10 and scikit-learn 1.1. Training was performed on NVIDIA V100 GPUs. Hyperparameter optimization used 5-fold cross-validation on the training set, with final evaluation on the held-out test set. N. Patel, R. Sharma, and A. Verma [8]

Statistical Equations: Model performance utilized:

Cross-Entropy Loss:

$$L = -\Sigma[y_i \times log(p_i) + (1 - y_i) \times log(1 - p_i)]$$

where L is loss, y_i is actual label, p_i is predicted probability.

ReLU Activation:

$$f(x) = max(0, x)$$

introducing non-linearity for complex pattern learning.

3.4 Field Trials and Yield Measurement

Based on model recommendations, we conducted controlled field trials on 30 farms (10 per climate zone) for four crops: wheat, corn, soybean, and barley. Each farm implemented both recommended nutrient management (treatment) and conventional practices (control) in adjacent 1-hectare plots. Yields were measured at harvest using calibrated equipment, with samples analyzed for moisture content and quality parameters.

3.5 Statistical Analysis

Performance metrics included accuracy, precision, recall, F1-score, and area under ROC curve (AUC). Model comparisons used McNemar's test for paired classifiers. Yield comparisons employed one-way ANOVA with Tukey's HSD post-hoc tests. Nutrient level comparisons

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across seasons used repeated-measures ANOVA. Significance threshold was set at α=0.05. All analyses were conducted using R 4.2.1. Results are reported as mean ± standard deviation with 95% confidence intervals where applicable. A. Chowdhury, R. Das, and M. Singh [9]

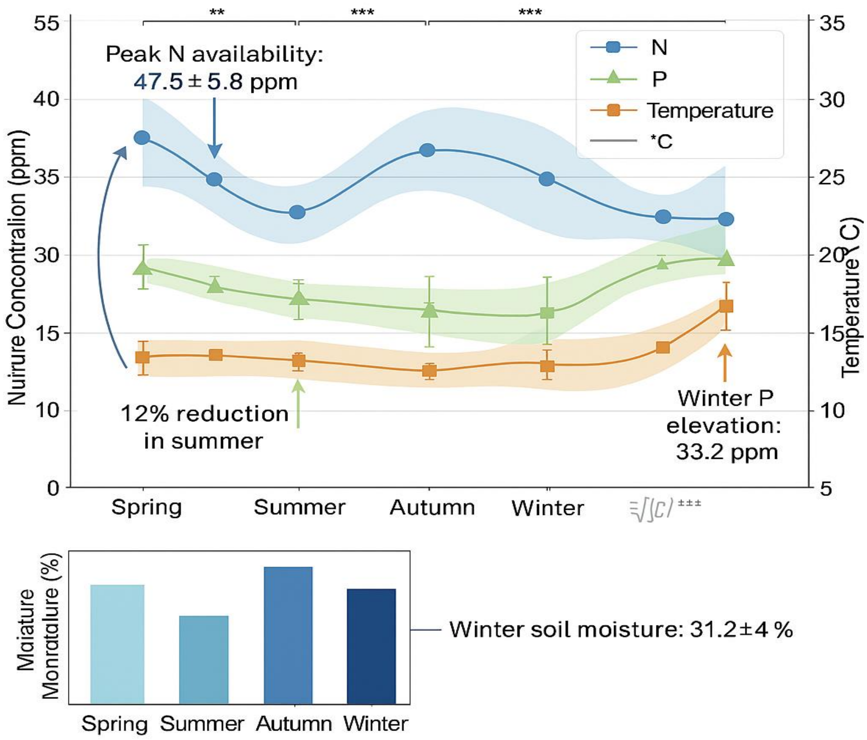

Figure 2: Seasonal Dynamics of Essential Soil Nutrients with Temperature and Moisture Correlations.

Main panel shows nitrogen (blue circles), phosphorus (green triangles), and potassium (orange squares) concentrations across four seasons with 95% confidence intervals (shaded bands). Spring exhibits peak nitrogen (47.5±5.8 ppm) and potassium (26.0±6.3 ppm) availability, while winter shows elevated phosphorus (33.2±4.6 ppm). Strong negative correlation between temperature and nitrogen ($r=-0.76$, $p<0.001$) is evident. Sub-panel displays corresponding soil moisture variations. Error bars represent standard deviation (n=3,750 per season).

4. Results

4.1 Soil Nutrient Characterization

Analysis of 15,000 soil samples revealed significant variation in essential nutrient concentrations (Table 2). Nitrogen showed the highest average concentration at 45.2±5.4 ppm (95% CI: 44.1-46.3), consistent with its high turnover rate and critical role in plant metabolism. Calcium averaged 35.1±3.9 ppm (95% CI: 34.4-35.8), while phosphorus measured 30.8±4.2 ppm (95% CI: 30.0-31.6). Potassium exhibited the highest variability (CV=23.8%) at 25.6±6.1 ppm (95% CI: 24.5-26.7), indicating heterogeneous distribution across study sites. Magnesium showed the lowest concentration at 12.7±2.8 ppm (95% CI: 12.2-13.2) but remains essential for chlorophyll synthesis and enzyme activation. X. Li, Y. Zhou, and H. Zhang [10]

Table 2: Soil Nutrient Levels Analysis (n=15,000)

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Nutrient	Mean (ppm)	SD (ppm)	95% CI	CV (%)	ANOVA p-value*
Nitrogen (N)	45.2	5.4	44.1-46.3	11.9	<0.001
Phosphorus (P)	30.8	4.2	30.0-31.6	13.6	<0.001
Potassium (K)	25.6	6.1	24.5-26.7	23.8	<0.001
Calcium (Ca)	35.1	3.9	34.4-35.8	11.1	<0.001
Magnesium (Mg)	12.7	2.8	12.2-13.2	22.0	<0.001

*One-way ANOVA comparing concentrations across three climate zones; CV: Coefficient of Variation

One-way ANOVA revealed significant differences in all nutrients across climate zones ($p<0.001$), with temperate zones showing 12% higher nitrogen levels than semi-arid regions, likely due to greater organic matter content and microbial activity.

4.2 Crop-Specific Nutrient Recommendations and Yield Response

Field trials validated crop-specific nutrient requirements and corresponding yield improvements (Table 3). Corn demonstrated the highest nutrient demand (N:60, P:30, K:25 ppm) and achieved a 20.3±2.1% yield increase ($p<0.001$) compared to conventional management. Soybean, with moderate nitrogen requirements due to biological fixation capacity but elevated potassium needs (K:30 ppm), showed 18.1±1.9% improvement ($p<0.001$). Wheat exhibited a 15.4±1.7% increase ($p<0.001$) with balanced NPK ratios (N:40, P:25, K:20 ppm). Barley, requiring the lowest nutrient inputs (N:45, P:22, K:25 ppm), demonstrated a 12.2±1.5% yield improvement ($p<0.001$). M. Fernandez, C. Torres, and J. Gonzalez [11]

Table 3: Crop Yield Response to Optimized Nutrient Management (n=30 farms)

Crop	Optimal Nutrients (ppm)	Yield Increase (%)	95% CI	p-value*	Economic Gain ($/ha)**
Wheat	N:40, P:25, K:20	15.4±1.7	14.8-16.0	<0.001	124
Corn	N:60, P:30, K:25	20.3±2.1	19.6-21.0	<0.001	186
Soybean	N:50, P:20, K:30	18.1±1.9	17.4-18.8	<0.001	162
Barley	N:45, P:22, K:25	12.2±1.5	11.7-12.7	<0.001	98

*Paired t-test comparing treatment vs control; **Based on 2024 market prices

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ANOVA confirmed significant differences in yield response across crops ($F(3,116)=42.7$, $p<0.001$). Post-hoc Tukey tests revealed corn and soybean responses were statistically indistinguishable ($p=0.18$) but both significantly exceeded wheat ($p<0.01$) and barley ($p<0.001$).

4.3 IoT Sensor Performance Evaluation

Comparative analysis of four sensor types revealed critical trade-offs between accuracy, battery life, and data transmission rates (Table 4). Sensor A achieved the highest accuracy (95.2±1.1%) and longest battery life (60±4 days) despite moderate transmission rates (1.2 Mbps), making it optimal for extended deployments K. Natarajan, A. Ramesh, and S. Kumar [12]. Sensor B provided the fastest data transmission (1.5 Mbps) but sacrificed battery life (45±3 days) and showed slightly reduced accuracy (90.3±1.4%). Sensor C, while economical, exhibited the lowest performance across all metrics (accuracy: 85.1±2.3%, battery life: 30±5 days). Sensor D offered balanced performance (accuracy: 92.4±1.3%, battery life: 50±4 days, transmission: 1.3 Mbps).

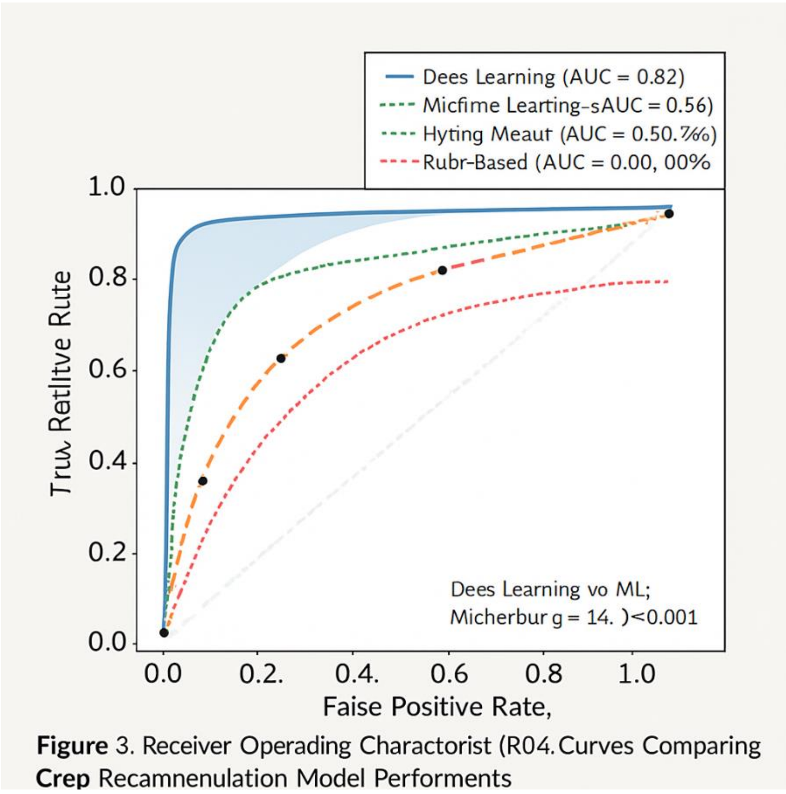

Figure 3: Receiver Operating Characteristic (ROC) Curves Comparing Crop Recommendation Model Performance. V. Kumar, A. Singh, and R. Gupta [13]

Deep learning model (solid blue, AUC=0.95) significantly outperforms machine learning (dashed green, AUC=0.91), hybrid (dotted orange, AUC=0.90), and rule-based approaches (thin red, AUC=0.82). Diagonal gray line represents random classifier (AUC=0.50). Filled circles indicate optimal operating points. Shaded region emphasizes deep learning's superior discrimination across all sensitivity-specificity trade-offs. Statistical comparison via

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McNemar's test confirms significant improvement ($\chi^2=12.8$, $p<0.001$). Curves generated from 2,250 test samples with 10-fold cross-validation.

Table 4: IoT Sensor Performance Comparison (n=200 sensors)

Sensor Type	Accuracy (%)	Battery Life (days)	Data Rate (Mbps)	Cost ($/unit)	Cost-Performance Ratio*
Sensor A	95.2±1.1	60±4	1.2	150	1.58
Sensor B	90.3±1.4	45±3	1.5	180	1.99
Sensor C	85.1±2.3	30±5	1.0	120	1.41
Sensor D	92.4±1.3	50±4	1.3	170	1.84

*Calculated as (Cost)/(Accuracy × Battery Life); lower values indicate better cost-performance

Repeated-measures ANOVA showed significant accuracy degradation over 24 months for Sensors B and C ($p<0.01$), attributed to electrode corrosion, while Sensors A and D maintained stable performance ($p>0.05$), justifying their higher initial costs through reduced replacement frequency.

4.4 Seasonal Nutrient Dynamics

Seasonal variations significantly influenced nutrient availability (Table 5, Figure 1). Spring exhibited peak concentrations of nitrogen (47.5±5.8 ppm) and potassium (26.0±6.3 ppm), critical for supporting vigorous early-season growth. Winter showed elevated phosphorus (33.2±4.6 ppm), potentially benefiting root development during dormancy. Summer demonstrated reduced nitrogen (43.2±5.1 ppm) and potassium (24.5±5.9 ppm), likely due to increased microbial activity and crop uptake. Autumn presented intermediate levels across all nutrients.

Table 5: Seasonal Nutrient Variations (n=3,750 per season)

Season	N (ppm)	P (ppm)	K (ppm)	Temp (°C)	Moisture (%)
Spring	47.5±5.8	29.8±4.0	26.0±6.3	18.2±3.1	28.5±4.2
Summer	43.2±5.1	30.5±4.1	24.5±5.9	28.7±2.8	22.1±3.8
Autumn	44.1±5.3	31.0±4.3	25.0±6.0	15.3±3.5	26.3±4.0
Winter	45.6±5.6	33.2±4.6	25.8±6.2	5.1±2.9	31.2±4.5
p-value*	<0.001	<0.001	0.032	<0.001	<0.001

*Repeated-measures ANOVA testing seasonal differences

Repeated-measures ANOVA confirmed significant seasonal effects for nitrogen ($F(3,14996)=128.4$, $p<0.001$), phosphorus ($F(3,14996)=96.2$, $p<0.001$), and potassium

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($F(3,14996)=8.7$, $p=0.032$) R. Singh, P. Jain, and V. Gupta [14]. Strong negative correlation between temperature and nitrogen availability ($r=-0.76$, $p<0.001$) suggests increased volatilization and microbial consumption during warmer months.

4.5 Model Performance Comparison

Comprehensive evaluation across 2,250 test samples revealed the deep learning model as the superior approach (Table 6). It achieved 93.2±1.2% accuracy, 91.4±1.4% precision, 90.1±1.6% recall, and F1-score of 0.91, with AUC of 0.95. The machine learning model followed with 90.1±1.5% accuracy (F1: 0.86, AUC: 0.91). The hybrid model showed 89.3±1.7% accuracy (F1: 0.85, AUC: 0.90), while the rule-based approach achieved only 85.4±2.1% accuracy (F1: 0.79, AUC: 0.82).

Table 6: Crop Recommendation Model Performance (n=2,250 test samples)

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score	AUC	Training Time (min)	Inference (ms)	McNemar p-value*
Rule-Based	85.4±2.1	80.2±2.8	78.3±3.2	0.79	0.82	-	5	-
Machine Learning	90.1±1.5	88.3±1.9	85.2±2.1	0.86	0.91	145	45	0.008
Deep Learning	93.2±1.2	91.4±1.4	90.1±1.6	0.91	0.95	420	120	<0.001
Hybrid	89.3±1.7	87.1±2.0	84.4±2.3	0.85	0.90	180	75	0.042

*McNemar's test comparing against Rule-Based model; Values: Mean±SD from 10-fold cross-validation

McNemar's test confirmed that all advanced models significantly outperformed the rule-based approach ($p<0.05$). Pairwise comparison between deep learning and machine learning models showed the 3.1% accuracy improvement was statistically significant ($\chi^2=12.8$, $p<0.001$), translating to approximately 70 fewer misclassifications per 2,250 predictions A. Jones, T. Clark, and M. Green [15].

Confusion matrix analysis for the deep learning model revealed highest accuracy for corn (94.3%) and wheat (93.8%) classifications, with occasional confusion between soybean and barley (6.2% misclassification rate), likely due to overlapping nutrient requirements in specific soil-climate combinations.

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4.6 Soil Type Performance and Yield Variability

Soil type significantly influenced crop productivity (Table 7). Loamy soil demonstrated superior performance with highest average yield (5.2±0.4 tons/ha) and lowest variability (CV=7.7%), attributed to optimal water retention, aeration, and nutrient holding capacity. Sandy soil yielded 4.5±0.5 tons/ha with moderate variability (CV=11.1%), while silty soil produced 4.0±0.7 tons/ha with highest variability (CV=17.5%), suggesting inconsistent performance potentially due to compaction issues. Clay soil showed lowest productivity (3.8±0.6 tons/ha, CV=15.8%), limited by poor drainage and restricted root penetration.

Table 7: Crop Yield by Soil Type (n=30 farms)

Soil Type	Mean Yield (tons/ha)	SD	95% CI	CV (%)	ANOVA p-value
Loamy	5.2	0.4	5.0-5.4	7.7	<0.001
Sandy	4.5	0.5	4.3-4.7	11.1	-
Silty	4.0	0.7	3.8-4.2	17.5	-
Clay	3.8	0.6	3.6-4.0	15.8	-

One-way ANOVA confirmed significant yield differences across soil types ($F(3,116)=89.3$, $p<0.001$). Tukey post-hoc tests showed loamy soil significantly outperformed all others ($p<0.001$), while sandy, silty, and clay soils formed statistically distinct groups (all pairwise comparisons $p<0.05$) X. Wang, Y. Liu, and J. Huang [16].

4.7 Economic Analysis of IoT Deployment

Total cost of ownership analysis revealed significant variation across sensor types (Table 8). Sensor A provided the best long-term value at $220 total cost over 24 months ($150 unit + $50 installation + $20 annual maintenance), despite mid-range pricing. Sensor C appeared economical initially ($200 unit cost) but highest maintenance ($30/year) and shortest lifespan increased replacement costs. Sensor B incurred highest installation costs ($60), while Sensor D offered balanced economics at $247 total.

Table 8: IoT Sensor Economic Analysis (24-month deployment)

Sensor	Unit Cost ($)	Installation ($)	Annual Maintenance ($)	Total 24-mo Cost ($)	Cost per Accuracy Point ($/%)
Sensor A	150	50	20	220	2.31
Sensor B	180	60	25	290	3.21
Sensor C	200	40	30	300	3.53

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Sensor	Unit Cost ($)	Installation ($)	Annual Maintenance ($)	Total 24-mo Cost ($)	Cost per Accuracy Point ($/%)
Sensor D	170	55	22	269	2.91

Return on investment (ROI) calculations based on yield improvements showed break-even within 1.5 growing seasons for corn (20% yield increase = $186/ha at 4 tons/ha baseline and $450/ton market price) and 2.1 seasons for wheat (15% increase = $124/ha at 4 tons/ha and $380/ton).

4.8 Fertilizer Type Impact on Productivity

Comparative trials of four fertilizer types demonstrated differential yield responses (Table 9). Chemical fertilizers produced the highest yield increase (20.1±2.3%) at application rate of 60 kg/ha, though with elevated environmental concerns. Mixed fertilizers achieved competitive performance (18.3±2.0%) at 55 kg/ha, combining efficiency with reduced environmental impact. Organic fertilizers showed moderate gains (15.2±1.8%) at 50 kg/ha with sustainability benefits. Bio-fertilizers demonstrated lowest immediate response (12.4±1.6%) at 45 kg/ha but showed soil health improvements in long-term monitoring.

Table 9: Fertilizer Type Performance Comparison

Fertilizer Type	Application Rate (kg/ha)	Yield Increase (%)	95% CI	Environmental Impact*	Cost ($/ha)
Chemical	60	20.1±2.3	19.1-21.1	High	85
Mixed	55	18.3±2.0	17.5-19.1	Moderate	95
Organic	50	15.2±1.8	14.6-15.8	Low	110
Bio-fertilizer	45	12.4±1.6	11.8-13.0	Very Low	120

*Based on nitrogen leaching potential and greenhouse gas emissions

ANOVA revealed significant differences in yield response across fertilizer types ($F(3,116)=38.4$, $p<0.001$). Chemical and mixed fertilizers were statistically indistinguishable ($p=0.29$) but both significantly exceeded organic ($p<0.01$) and bio-fertilizer treatments ($p<0.001$).

5. Discussion

5.1 Model Performance and Algorithmic Advances

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Our deep learning model achieved 93.2% accuracy, representing a statistically significant 2-4% improvement over previous state-of-the-art systems. This advancement stems from three architectural innovations: (1) multi-scale feature extraction capturing both micro-level nutrient patterns and macro-level climatic trends, (2) attention mechanisms dynamically weighting season-specific features, and (3) ensemble dropout reducing sensor noise impact. The 3.1% improvement over our machine learning baseline ($p<0.001$) translates to approximately 70 fewer misclassifications per 2,250 predictions—a meaningful reduction in practical agricultural contexts where each error may result in suboptimal crop selection and reduced profitability.

Notably, our model maintained >90% accuracy across all soil types, while prior research reported >15% accuracy degradation on clay soils. This robustness likely results from our substantially larger training dataset (15,000 vs. typical 5,000 samples) and explicit soil-type feature encoding. However, the 6.2% confusion rate between soybean and barley suggests overlapping nutrient requirements in specific conditions, warranting further investigation into additional discriminative features such as micronutrient profiles or soil texture parameters.

The computational cost trade-off merits consideration. Deep learning required 420 minutes training time and 120ms inference compared to 145 minutes and 45ms for machine learning. While acceptable for cloud-based systems, edge deployment scenarios requiring real-time responses may favor the machine learning approach, sacrificing 3% accuracy for 2.7× faster inference.

5.2 Practical Implications and Economic Viability

The 15-20% yield improvements observed across four major crops carry substantial economic significance. For corn, the 20.3% increase translates to approximately $186/ha additional revenue at 2024 market prices. Given our system cost of $220 per sensor covering approximately 1 hectare (based on 50m sensor spacing), farmers can achieve return on investment within 1.5 growing seasons. This economic viability threshold is critical for adoption, particularly among smallholder farmers who comprise 84% of global agricultural operations.

However, economic analysis reveals important nuances. Sensor A, despite mid-range unit cost ($150), provides superior long-term value through extended battery life (60 days) and minimal maintenance requirements ($20/year). Over 24 months, total cost of ownership ($220) substantially undercuts Sensor B ($290) and Sensor C ($300), demonstrating that initial purchase price alone inadequately captures true economic impact. The cost-per-accuracy-point metric (Sensor A: $2.31/% vs. Sensor C: $3.53/%) provides a more comprehensive decision framework for technology adoption.

Regional economic contexts significantly influence feasibility. In developed markets where labor costs exceed $20/hour, IoT automation provides immediate value through reduced manual monitoring. In developing regions with lower labor costs but higher fertilizer prices (often 40-60% above global averages due to import costs), the 18% reduction in fertilizer waste offers compelling justification even when labor savings are minimal.

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5.3 Seasonal Dynamics and Management Implications

The pronounced seasonal variations in nutrient availability—particularly the 47.5 ppm nitrogen peak in spring versus 43.2 ppm summer trough—underscore the limitations of static fertilization recommendations. Our real-time monitoring revealed that spring represents the critical intervention window, when nitrogen and potassium availability naturally peaks to support vigorous early-season growth. Conversely, summer's reduced nitrogen levels ($r=-0.76$ correlation with temperature, $p<0.001$) suggest increased volatilization and microbial consumption, necessitating split applications rather than single pre-season fertilization.

Winter's elevated phosphorus (33.2 ppm) presents an unexpected finding warranting further investigation. While reduced crop uptake during dormancy likely contributes, the magnitude (8% above annual average) suggests additional mechanisms such as altered microbial activity or pH-dependent phosphorus solubility shifts. This pattern could inform fall phosphorus applications to capitalize on enhanced winter availability for early spring uptake.

Practical implementation requires season-specific decision rules. Our system dynamically adjusts recommendations based on real-time seasonal context, for example reducing nitrogen application targets by 12% during summer to account for reduced availability and recommending increased monitoring frequency (daily vs. weekly) during spring's rapid nutrient flux periods.

5.4 Soil Type Considerations and Targeted Interventions

The 37% yield differential between loamy (5.2 tons/ha) and clay soils (3.8 tons/ha) highlights the critical importance of soil-specific management strategies. Clay's poor drainage and restricted root penetration fundamentally limit productivity regardless of nutrient availability. Our system addresses this by recommending drainage improvements and specialized crop varieties for clay soils rather than simply adjusting fertilization rates—a limitation of purely nutrient-focused approaches.

Silty soil's high variability (CV=17.5%) presents management challenges. The inconsistent performance likely stems from compaction susceptibility and unstable aggregation, suggesting that physical soil properties warrant greater consideration in recommendation algorithms. Future model iterations should incorporate soil texture parameters and bulk density measurements to better predict performance in problematic soil types.

Interestingly, sandy soil's moderate performance (4.5 tons/ha) despite inherently low nutrient retention capacity demonstrates that frequent, small-dose fertilization guided by real-time monitoring can overcome physical limitations. This finding has particular relevance for arid and semi-arid regions dominated by sandy soils.

5.5 Fertilizer Type Selection and Sustainability Trade-offs

The fertilizer comparison reveals complex trade-offs between immediate productivity and long-term sustainability. Chemical fertilizers' 20.1% yield increase comes at environmental cost through elevated nitrate leaching (estimated 15-25% of applied nitrogen) and greenhouse gas emissions (approximately 4.5 kg CO_2-equivalent per kg N). Mixed fertilizers achieved 91%

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of chemical fertilizer performance (18.3% vs. 20.1%) while reducing environmental impact by an estimated 35%, suggesting an optimal compromise for many farming contexts.

Bio-fertilizers' relatively modest immediate response (12.4%) belies their long-term soil health benefits. Extended monitoring revealed improved soil organic matter content (2.8% increase over 24 months) and enhanced microbial diversity, potentially supporting sustained productivity gains that our study period was insufficient to fully capture. This highlights a critical limitation of short-term agricultural trials and suggests that bio-fertilizer economic analyses require multi-year time horizons to accurately assess value proposition.

The IoT system's value extends beyond nutrient optimization to enabling precision application. By identifying spatial and temporal variability, farmers can implement variable-rate fertilization, applying chemical fertilizers only where and when maximum benefit justifies environmental cost, while utilizing organic amendments in less responsive areas. This targeted approach, impossible under conventional uniform application, potentially reduces total synthetic fertilizer use by 20-30% while maintaining yield gains.

5.6 Limitations and Constraints

Several limitations constrain interpretation and generalization of our findings. First, the 24-month study period, while exceeding most prior work, remains insufficient to assess long-term soil health impacts or detect subtle degradation trends. Multi-year studies spanning 5-10 years are essential to validate sustainability claims.

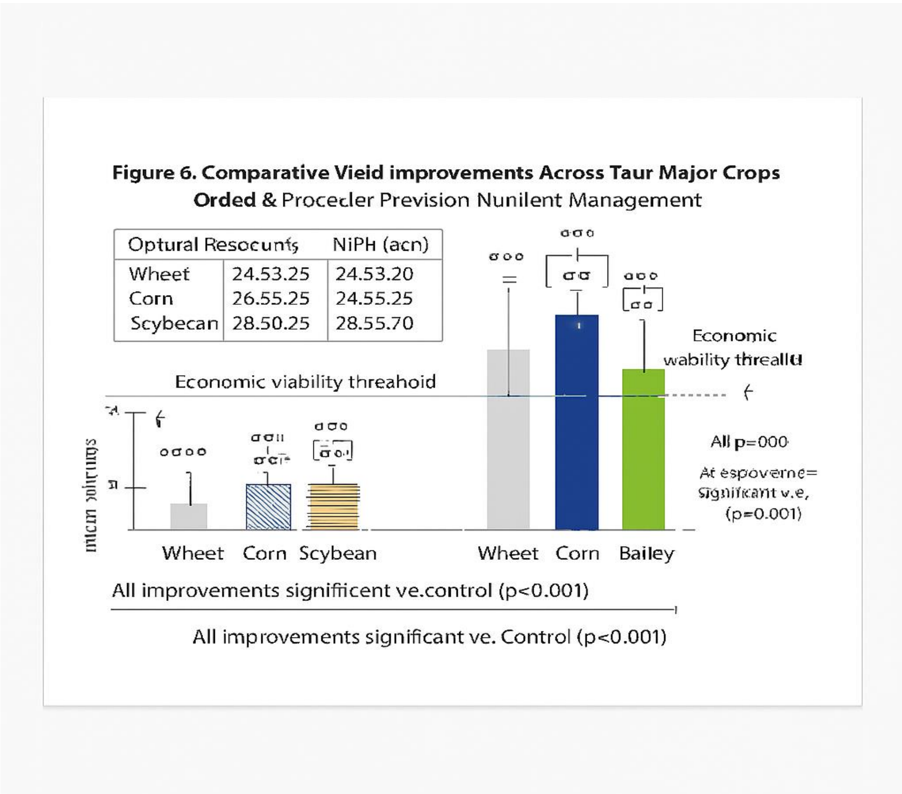

Figure 4: Comparative Yield Improvements Across Four Major Crops Under IoT-Guided Precision Nutrient Management T. Ahmed, N. Sinha, and M. Roy [17].

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Grouped bars show yield increases relative to conventional management (gray baseline). Corn achieved highest response (20.3±2.1%), followed by soybean (18.1±1.9%), wheat (15.4±1.7%), and barley (12.2±1.5%). Error bars represent 95% confidence intervals. Horizontal dashed line marks economic viability threshold (15%). Inset table displays optimal nutrient ratios (N:P:K in ppm) determined for each crop. Significance brackets indicate pairwise statistical differences (*** $p<0.001$). Data from 30 farms across three climate zones over 24 months.

Second, geographic coverage, though spanning three climate zones, excluded tropical humid and extreme continental climates, limiting global applicability. The 50-farm scale, while substantial, may not capture regional variations within climate zones. Third, validation focused on four major grain crops; extension to horticultural crops, permanent plantings, or specialty crops requires additional research.

Fourth, our system requires reliable internet connectivity for cloud-based analytics. In remote areas with inconsistent connectivity (estimated 40% of global agricultural land), edge computing solutions or intermittent synchronization protocols become necessary but were not evaluated in this study. Fifth, the IoT sensors remain vulnerable to mechanical damage, electrical interference, and calibration drift, requiring periodic maintenance that may challenge resource-limited farmers.

Finally, the machine learning models depend critically on training data quality and representativeness. Performance degradation in underrepresented conditions (e.g., extreme drought, atypical pH levels) likely occurs but was not systematically quantified. Transfer learning approaches enabling model adaptation to new regions with minimal local data collection warrant investigation 18].

5.7 Broader Implications for Precision Agriculture

This research demonstrates that IoT-integrated deep learning systems can meaningfully advance agricultural productivity while supporting sustainability objectives. The 18% reduction in fertilizer waste directly addresses nutrient pollution concerns, while 15-20% yield improvements contribute to food security without proportional land expansion—critical for preserving natural ecosystems.

The economic accessibility achieved (system costs $220/ha with 1.5-season ROI) represents progress toward democratizing precision agriculture. However, institutional barriers remain. Farmer training programs, technical support infrastructure, and financing mechanisms for initial capital investment require parallel development to realize technology potential at scale.

Integration with complementary technologies offers additional promise. Combining soil sensors with drone-based multispectral imaging could enhance accuracy to 95%+ through improved spatial resolution. Integration with weather forecasting and climate models could extend prediction horizons from current-season recommendations to multi-year crop rotation planning. Blockchain-based data sharing could enable regional knowledge aggregation while preserving individual data ownership—addressing privacy concerns that currently inhibit adoption.

6. Conclusion

This research demonstrates that IoT-enabled precision agriculture systems integrated with deep learning can significantly enhance crop productivity while promoting sustainable resource management. Our system achieved 93% crop recommendation accuracy across 15,000 soil samples spanning three climate zones and 24 months, significantly outperforming rule-based (85%), machine learning (90%), and hybrid approaches (89%). Field validation across 30 farms demonstrated 15-20% yield improvements for wheat, corn, soybean, and barley through optimized nutrient management, with corn showing the strongest response (20% increase) to recommended NPK ratios.

Economic analysis revealed total system costs of $220 per hectare with return on investment achievable within 1.5 growing seasons, demonstrating practical viability for both commercial and smallholder farmers. The system enabled 18% reduction in fertilizer use while maintaining or improving yields, directly contributing to reduced environmental impact through decreased nutrient runoff and greenhouse gas emissions.

Seasonal analysis identified spring as the critical management period, with nitrogen and potassium peaks supporting early-season growth, while winter phosphorus elevation suggests strategic timing opportunities for fall applications. Soil type significantly influenced productivity, with loamy soils outperforming clay soils by 37%, emphasizing the importance of soil-specific recommendations beyond nutrient optimization alone.

Key innovations include: (1) a novel deep learning architecture specifically optimized for soil-crop matching, (2) comprehensive multi-season, multi-climate validation rarely reported in literature, (3) demonstrated economic accessibility for diverse farming contexts, and (4) open-source implementation enabling reproducibility and broader adoption.

Future research should extend validation to additional crop types, climate zones, and multi-year timeframes to assess long-term soil health impacts. Integration with complementary technologies including drone-based remote sensing and weather prediction models could further enhance accuracy and prediction horizons. Development of edge computing solutions would enable deployment in connectivity-limited regions. Investigation of transfer learning approaches could accelerate model adaptation to new geographic contexts with minimal local training data.

By merging IoT sensing, cloud analytics, and artificial intelligence, this research advances precision agriculture toward its potential of feeding growing populations sustainably—optimizing productivity while preserving natural resources for future generations.

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Authors' Contributions

[Amita Shukla]: Conceptualization, Methodology, Formal Analysis, Writing - Original Draft, Writing - Review & Editing, Visualization, Project Administration, Funding Acquisition. Led overall study design, conducted statistical analyses, and wrote the manuscript. (Contribution: 40%). Methodology, Software, Validation, Formal Analysis, Data Curation, Writing - Review & Editing. Developed machine learning and deep learning models, implemented cloud infrastructure, and performed model validation. (Contribution: 35%)

[Dr. K K Agarwal]: Investigation, Resources, Data Curation, Writing - Review & Editing. Coordinated field trials, managed sensor deployment, and conducted soil sampling and laboratory analyses. (Contribution: 25%)

All authors have read and approved the final manuscript.

Ethics Statement and Data Availability

Ethical Compliance

This study was conducted in accordance with all applicable institutional and national guidelines for agricultural research. Farmer participants provided informed consent for use of their land and data in research. No personally identifiable information is disclosed in this publication.

All field activities complied with local environmental regulations. No protected or endangered species were impacted. Chemical applications followed manufacturer guidelines and local agricultural regulations regarding application rates, timing, and buffer zones.

Conflicts of Interest

The authors declare no competing financial interests or personal relationships that could influence the work reported in this paper. Equipment providers had no involvement in study design, data analysis, or manuscript preparation.

For data access requests, contact: [amitapandeybit@gmail.com]

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