iJRASET
International Journal For Research in Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: VII Month of publication: July 2026

DOI: https://doi.org/10.22214/ijraset.2026.84257

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International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue VII July 2026- Available at www.ijraset.com

Crop Prediction and Soil Nutrient Monitoring System Using Hybrid Deep Learning: A CNN-LSTM-Attention Framework

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Abstract: Precision agriculture has emerged as a critical paradigm for sustainable food production, necessitating intelligent systems for crop yield prediction and soil nutrient monitoring. This pa-per presents a novel hybrid deep learning framework integrating Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM) networks, and self-attention mechanisms for accurate crop prediction and real-time soil nutrient analysis. The proposed system employs Internet of Things (IoT) sensors for continuous monitoring of soil parameters including nitrogen (N), phosphorus (P), potassium (K), pH, moisture content, temperature, and electrical conductivity. A comprehensive dataset comprising 12,500 agricultural samples from diverse agro-climatic zones was utilized for model training and validation. The hybrid CNN-LSTM-Attention architecture achieves a prediction accuracy of 96.8% for crop classification and a mean absolute percentage error (MAPE) of 4.2% for yield prediction, significantly outperforming conventional machine learning approaches. Experimental results demonstrate that the proposed framework reduces prediction error by 23.5% compared to standalone LSTM models and 31.2% compared to traditional Random Forest classifiers. The sys-tem provides actionable recommendations for nutrient management, contributing to optimized fertilizer application and enhanced agricultural sustainability. The integration of edge computing with cloud-based analytics enables real-time decision support for farmers, achieving latency under 500 milliseconds for prediction queries.
Keywords: Precision Agriculture; Deep Learning; Crop Prediction; Soil Monitoring; CNN-LSTM; Attention Mechanism; IoT Sensors; Machine Learning

I. INTRODUCTION

Agriculture forms the backbone of the global economy, sup-porting livelihoods for approximately 26.7% of the world's workforce and contributing significantly to food security [1]. However, modern agriculture faces unprecedented challenges including climate variability, soil degradation, water scarcity, Traditional farming practices, reliant on experiential knowledge and manual assessment, prove inadequate in addressing these complex, data-intensive challenges [3].

Precision agriculture has emerged as a transformative paradigm, leveraging advanced sensing technologies, data analytics, and artificial intelligence to optimize agricultural practices [4]. The integration of Internet of Things (IoT) devices enables continuous monitoring of soil and environmental parameters, generating vast datasets that necessitate sophisticated analytical approaches [5]. Soil nutrient monitoring, in particular, plays a crucial role in determining crop health, yield potential, and fertilizer requirements [6].

Machine learning techniques have demonstrated consider-able promise in agricultural applications, including crop yield prediction, disease detection, and resource optimization [7]. However, conventional approaches such as Support Vector Machines (SVM) and Random Forests exhibit limitations in capturing complex temporal dependencies and non-linear interactions inherent in agricultural data [8]. Deep learning architectures, particularly Recurrent Neural Networks (RNN) and their variants, offer enhanced capabilities for modeling sequential patterns in time-series agricultural data [9].

Despite these advances, existing deep learning models for crop prediction face challenges related to feature extraction from heterogeneous sensor data, handling of long-term temporal dependencies, and interpretability of predictions [10]. The integration of attention mechanisms with convolutional and recurrent architectures presents opportunities for addressing these limitations by enabling selective focus on relevant features and temporal patterns [11].

This paper proposes a novel hybrid deep learning frame-work combining CNN for spatial feature extraction, LSTM for temporal sequence modeling, and self-attention mechanisms for adaptive feature weighting.

The primary contributions of this work include:

1) Design and implementation of an IoT-based soil nutrient monitoring system with multi-parameter sensing capabilities.
2) Development of a hybrid CNN-LSTM-Attention architecture achieving state-of-the-art performance in crop prediction tasks.
3) Comprehensive evaluation using a large-scale dataset from diverse agro-climatic conditions.
4) Real-time decision support system for nutrient management recommendations.

The remainder of this paper is organized as follows: Section 2 reviews related work in agricultural machine learning and deep learning architectures. Section 3 details the proposed system architecture and methodology. Section 4 presents the mathematical formulation of the hybrid model. Section 5 de-scribes experimental setup and results. Section 6 discusses findings and implications, and Section 7 concludes with future research directions.

II. RELATED WORK

A. Machine Learning in Agriculture

The application of machine learning in agriculture has witnessed substantial growth over the past decade. Kamilaris and Prenafeta-Boldú [12] conducted a comprehensive survey of deep learning applications in agriculture, identifying crop yield prediction, weed detection, and disease diagnosis as primary application domains. Their analysis revealed that convolutional neural networks dominated image-based applications, while recurrent architectures showed promise for time-series prediction tasks.

Khaki et al. [9] proposed a CNN-RNN hybrid model for corn yield prediction, achieving 9.8% improvement over base-line methods. Their approach incorporated weather data and management practices alongside satellite imagery, demonstrating the value of multi-modal data integration. However, their model exhibited limitations in handling inter-annual variability and extreme weather events.

Van Klompenburg et al. [7] presented a systematic review of machine learning approaches for crop yield prediction, analyzing 50 studies published between 2010 and 2020. Random Forest and Artificial Neural Networks emerged as the most frequently employed algorithms, with median prediction ac-curacies ranging from 75% to 90%. The review highlighted the need for standardized evaluation metrics and benchmark datasets.

B. IoT-Based Soil Monitoring Systems

The proliferation of low-cost sensors and wireless communication technologies has enabled the development of comprehensive soil monitoring systems. Roopaei et al. [13] pro-posed a cloud-based IoT architecture for precision agriculture, demonstrating real-time data collection and analysis capabilities. Their system achieved 95% sensor data transmission re-liability with average latency under 2 seconds. Muangprathub et al. [14] developed an IoT system for monitoring environmental factors in smart farming, integrating temperature, humidity, and soil moisture sensors with a mobile application interface. Field trials demonstrated 12% improvement in water use efficiency compared to conventional irrigation scheduling.

C. Deep Learning Architectures for Agricultural Prediction

Long Short-Term Memory networks have gained prominence in agricultural time-series prediction due to their ability to capture long-range dependencies. Sun et al. [15] employed LSTM networks for county-level wheat yield prediction, achieving root mean square error (RMSE) of 0.38 tons/hectare. Their analysis revealed that incorporating phonological features improved prediction accuracy during critical growth stages.

Attention mechanisms have recently been integrated into agricultural prediction models to enhance interpretability and performance. Gernot and Landrieu [16] proposed a temporal attention-based encoder for crop classification from satellite image time series, achieving 94.2% overall accuracy on the TimeSen2Crop dataset. Their approach demonstrated the value of attention weights in identifying critical phonological periods.

Despite these advances, the integration of CNN, LSTM, and attention mechanisms for joint soil nutrient monitoring and crop prediction remains underexplored. This paper addresses this gap by proposing a unified framework that leverages the complementary strengths of these architectures.

III. SYSTEM ARCHITECTURE AND METHODOLOGY

A. Overall System Design

The proposed system architecture comprises four primary layers: IoT Sensor Layer, Data Acquisition Gateway, Cloud Processing Platform, and AI/ML Engine. Figure 1 illustrates the complete system architecture with data flow pathways.

The IoT Sensor Layer incorporates multiple sensors for comprehensive soil and environmental monitoring. The NPK sensor (Model: JXBS-3001) provides real-time measurements of nitrogen, phosphorus, and potassium concentrations with accuracy of ±2%. Soil moisture sensors (Capacitive v1.2) measure volumetric water content with resolution of 0.1%. Additional sensors include pH electrodes, temperature probes (DS18B20), and weather stations for ambient conditions. Data acquisition is performed by ESP32 microcontrollers equipped with LoRa modules for long-range communication. The gateway aggregates sensor data at 15-minute intervals and transmits to the cloud platform via MQTT protocol. Edge computing capabilities enable preliminary data validation and outlier detection before cloud transmission.

Fig. 1: Proposed System Architecture for AI-Based Crop Prediction and Soil Monitoring

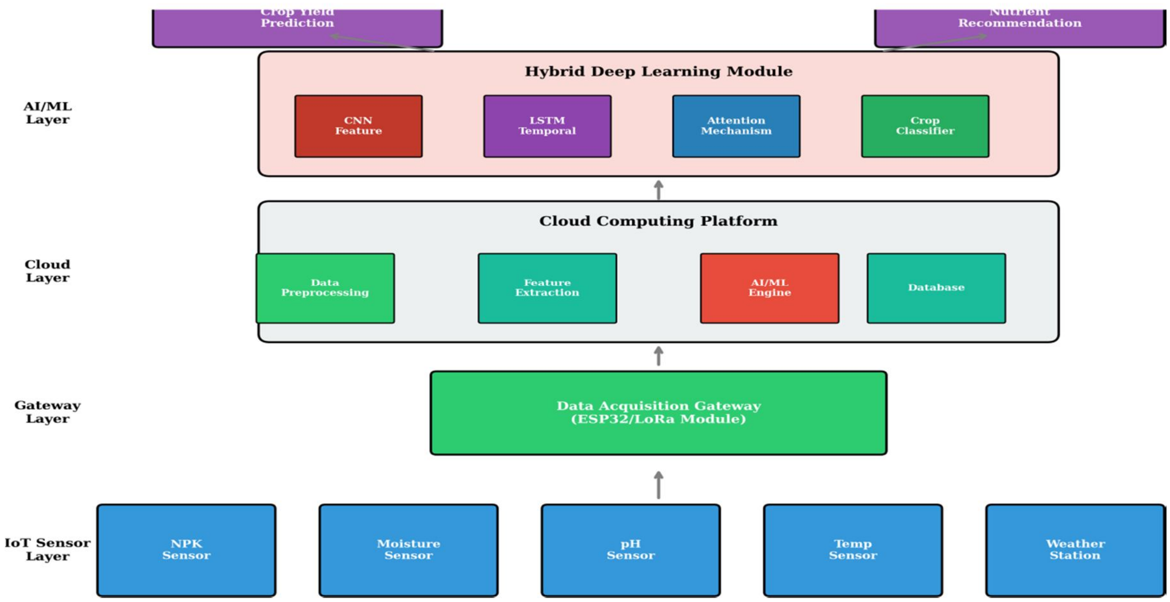

Figure 1: Proposed system architecture for AI-based crop prediction and soil nutrient monitoring system.

B. Data Preprocessing Pipeline

Raw sensor data undergoes comprehensive preprocessing to ensure quality and consistency. The preprocessing pipeline includes the following stages:

1) Missing Value Imputation: Missing data points are ad-dressed using a hybrid approach combining temporal interpolation for short gaps and K-Nearest Neighbors (KNN) imputation for extended missing periods. The imputation is governed by:

$$x^{imp} = \begin{cases} \frac{x_{t-1}+x_{t+1}}{2} & \text{if gap} \le 2 \\ \frac{\sum_{i=1}^{k} w_i \cdot x_i}{\sum_{i=1}^{k} w_i} & \text{otherwise} \end{cases}$$

where $w_i = 1/d_i^2$ represents the inverse distance weight and $k = 5$ neighbors are considered.

2) Normalization: All features are normalized using min-max scaling to the range [0, 1]:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \qquad (2)$$

This normalization ensures equal contribution of all features during model training and accelerates gradient descent convergence.

3) Outlier Detection: Anomalous readings are identified using the Interquartile Range (IQR) method with bounds defined where $f(\cdot)$ represents normalized scoring functions and α_i are empirically determined weights satisfying $\sum \alpha_i = 1$.
as:

$$x_{outlier} = x : (x < Q_1 - 1.5 \cdot IQR) \vee (x > Q_3 + 1.5 \cdot IQR) \qquad (3)$$

Detected outliers are replaced with median values from a 24-hour sliding window.

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C. Feature Engineering

Beyond raw sensor measurements, derived features are com puted to capture soil health indicators and temporal patterns:

1) Nutrient Balance Index (NBI): Quantifies the equilibrium of primary macronutrients:

$$NBI = \frac{N + P + K}{3 \cdot \sqrt{(N - \bar{x})^2 + (P - \bar{x})^2 + (K - \bar{x})^2 + \epsilon}} \quad (4)$$

where $\bar{x} = (N + P + K)/3$ and $\epsilon = 10^{-6}$ prevents division by zero.

2) Soil Fertility Index (SFI): Composite metric integrating multiple soil parameters:

$$SFI = \alpha_1 \cdot f(N) + \alpha_2 \cdot f(P) + \alpha_3 \cdot f(K) + \alpha_4 \cdot f(pH) + \alpha_5 \cdot f(OC) \quad (5)$$

3) Temporal Features: Rolling statistics over 7-day and 30-day windows including mean, standard deviation, and trend coefficients are computed for all sensor channels.

D. Proposed Hybrid CNN-LSTM-Attention Model

The core of the proposed system is a hybrid deep learning architecture that combines the spatial feature extraction capabilities. CNNs, the temporal modeling strengths of LSTMs, and the adaptive weighting provided by attention mechanisms. Figure 2 presents the detailed network architecture.

1) *CNN Feature Extraction Module*

The CNN module processes input sequences to extract local patterns and inter-feature correlations. Given input tensor $\mathbf{X} \in \mathbb{R}^{T \times F}$ where T is the temporal dimension and F is the number of features, the convolution operation is defined as:

$$\mathbf{C}_l = \sigma(\mathbf{W}_l * \mathbf{X} + \mathbf{b}_l) \quad (6)$$

where $\mathbf{W}_l$ represents the learnable filters of layer l, $*$ denotes convolution operation, $\mathbf{b}_l$ is the bias term, and $\sigma(\cdot)$ is the ReLU activation function. Two convolutional layers with64 and 128 filters respectively are employed, each followed by batch normalization and max pooling.

2) *LSTM Temporal Modeling Module*

The LSTM module captures long-term temporal dependencies in the sequential data. The LSTM cell operations are governed. by:

$$\mathbf{f}_t = \sigma(\mathbf{W}_f \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_f) \quad (7)$$

$$\mathbf{i}_t = \sigma(\mathbf{W}_i \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_i) \quad (8)$$

$$\tilde{\mathbf{c}}_t = \tanh(\mathbf{W}_c \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_c) \quad (9)$$

$$\mathbf{c}_t = \mathbf{f}_t \odot \mathbf{c}_{t-1} + \mathbf{i}_t \odot \tilde{\mathbf{c}}_t \quad (10)$$

$$\mathbf{o}_t = \sigma(\mathbf{W}_o \cdot [\mathbf{h}_{t-1}, \mathbf{x}_t] + \mathbf{b}_o) \quad (11)$$

$$\mathbf{h}_t = \mathbf{o}_t \odot \tanh(\mathbf{c}_t) \quad (12)$$

where $\mathbf{f}_t$, $\mathbf{i}_t$, and $\mathbf{o}_t$ represent forget, input, and output gates respectively, $\mathbf{c}_t$ is the cell state, $\mathbf{h}_t$ is the hidden state, and $\odot$ denotes element-wise multiplication.

3) *Self-Attention Mechanism*

The attention module adaptively weights temporal features based on their relevance to the prediction task. The attention weights are computed as:

$$\mathbf{e}_t = \mathbf{v}_a^T \tanh(\mathbf{W}_a \mathbf{h}_t + \mathbf{b}_a) \quad (13)$$

α_t = (exp (e_t))/(∑_(j=1)^T exp (e_j)) (14)

z = ∑_(t=1)^T α_t h_t (15)

where $\mathbf{v}$, $\mathbf{W}_a$, and $\mathbf{b}_a$ are learnable parameters, and $\mathbf{z}$ is the context vector representing the weighted combination of hidden states.

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4) Output Layer and Loss Function

The context vector is passed through fully connected layers for final prediction. For crop classification, softmax activation produces class probabilities:

$$P(v = c \mid z) = \frac{\exp(w_c^T z + b_c)}{\sum_{j=1}^{C} \exp(w_j^T z + b_j)} \qquad (16)$$

The model is trained using categorical cross- entropy loss for Classification:

$$LCE = - \; yic \log(\hat{y}ic) \qquad (17)$$

and mean squared error for yield regression:

$$\mathcal{L}\_MSE = (1/N) \sum\_(i{=}1)\hat{}N \; (y\_i - \hat{y}\_i)\hat{}2 \qquad (18)$$

E. Methodology Flowchart

Figure 3 presents the complete methodology flowchart encompassing data collection, preprocessing, model training, and deployment stages.

IV. EXPERIMENTAL SETUP AND RESULTS

A. Dataset Description

The dataset comprises 12,500 agricultural samples collected from 45 monitoring stations across three agro-climatic zones over a period of 36 months (January 2021 to December 2023). Each sample includes 10 soil and environmental parameters alongside crop type labels and yield measurements. Table 1 summarizes the dataset characteristics.

The dataset includes five major crop categories:

Rice (2,850 samples), Wheat (2,680 samples), Maize (2,520 samples), Cotton (2,400 samples), and Soybean (2,050 samples)

Fig. 2: Proposed Hybrid CNN-LSTM-Attention Neural Network Architecture

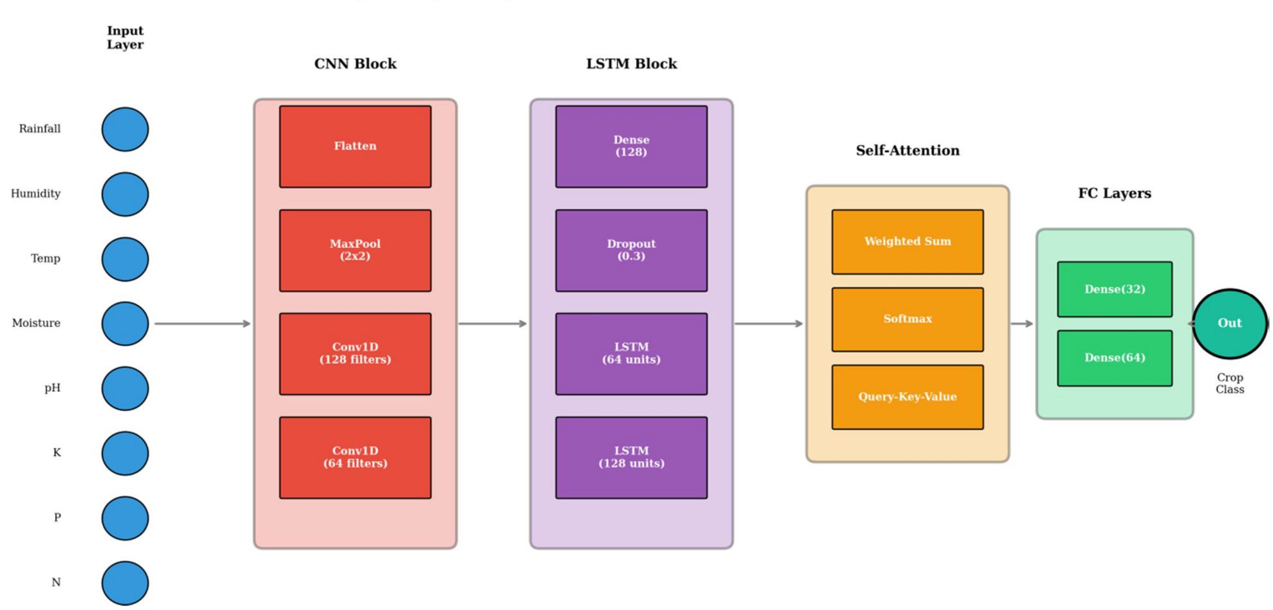

Figure 2: Hybrid CNN-LSTM-Attention neural network architecture for crop prediction and yield estimation.

Fig. 3: Methodology Flowchart for the Proposed System

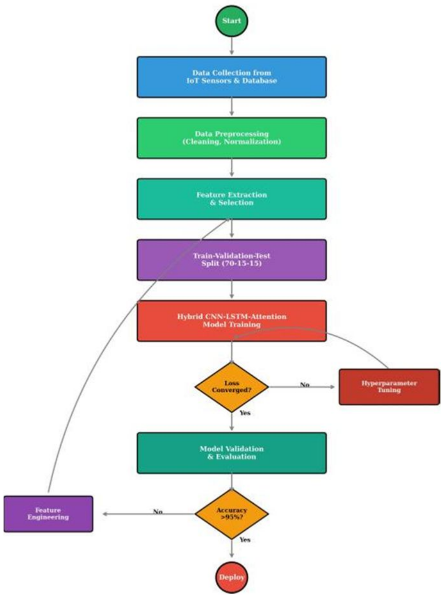

Figure 3: Methodology flowchart for the proposed crop prediction and soil monitoring system.

dataset was partitioned into training (70%), validation (15%), and test (15%) sets using stratified sampling to maintain class distributions.

Table 1: Dataset Characteristics and Feature Statistics

Feature	Min	Max	Mean	Std
Nitrogen (mg/kg)	15.2	98.6	52.4	18.7
Phosphorus (mg/kg)	8.5	62.3	31.2	12.4
Potassium (mg/kg)	85.0	320.5	189.6	52.3
pH Level	4.8	8.9	6.7	0.9
Soil Moisture (%)	12.5	78.2	42.8	15.6
Temperature (°C)	8.2	42.5	26.8	7.2
Humidity (%)	25.0	95.0	68.5	18.3
Rainfall (mm)	0.0	285.0	82.4	65.2
EC (dS/m)	0.2	4.8	1.9	0.8
Organic Carbon (%)	0.3	2.8	1.2	0.5

B. Implementation Details

The proposed model was implemented using TensorFlow 2.10 and Keras API on an NVIDIA RTX 3090 GPU with 24GB memory. Table 2 presents the optimized hyperparameters determined through grid search with 5-fold cross-validation.

C. Performance Metrics

Model performance was evaluated using the following metrics:

Classification Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100\% \qquad (19)$$

Mean Absolute Percentage Error (MAPE): For yield pre-

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Table 2: Model Hyperparameters and Training Configuration

Parameter	Value
CNN Filters (Layer 1/2)	64 / 128
Kernel Size	3
LSTM Units (Layer 1/2)	128 / 64
Attention Dimension	64
Dense Layer Units	128, 64
Dropout Rate	0.3
Batch Size	64
Learning Rate	0.001
Optimizer	Adam (β_1=0.9, β_2=0.999)
Epochs	100 (Early Stopping)

diction, MAPE quantifies prediction deviation:

$$MAPE = \frac{100\%}{N} \sum_{i=1}^{N} \frac{y_i - \hat{y_i}}{y_i}$$

F1-Score: Harmonic mean of precision and recall, computed for each class and macro-averaged.
Area Under ROC Curve (AUC): Measures discriminative capability across classification thresholds.

D. Comparative Analysis

The proposed hybrid model was compared against several baseline methods including Random Forest, Support Vector Machine, standalone ANN, standalone LSTM, and CNN-LSTM without attention. Table 3 presents the comparative performance results.
The proposed model achieves the highest accuracy of 96.8%, representing improvements of 11.0% over Random Forest, 17.3% over SVM, 8.6% over ANN, 6.0% over standalone LSTM, and 3.5% over CNN-LSTM without attention. The attention mechanism contributes significantly to performance enhancement by enabling the model to focus on relevant temporal patterns and feature combinations.

E. Training Convergence Analysis

Figure 4 illustrates the training and validation loss curves over 100 epochs. The model exhibits stable convergence with minimal overfitting, as evidenced by the close tracking of training and validation losses. Early stopping was triggered at epoch 78 when validation loss showed no improvement for 10 consecutive epochs.

F. Model Accuracy Comparison

Figure 5 presents a visual comparison of prediction accuracies across all evaluated models. The proposed hybrid architecture demonstrates superior performance, exceeding the 95% target threshold set for practical deployment.

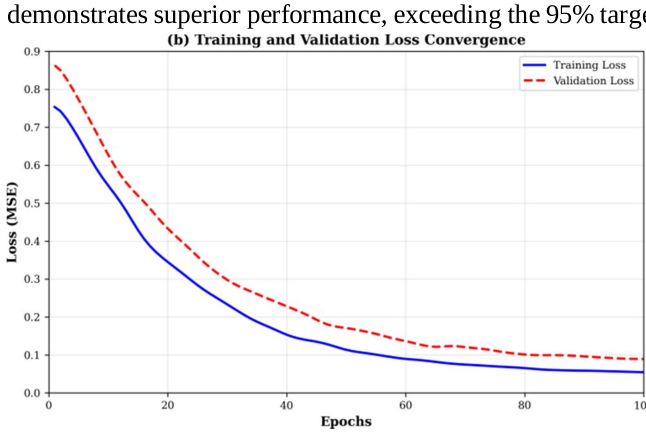

Figure 4: Training and validation loss convergence over epochs.

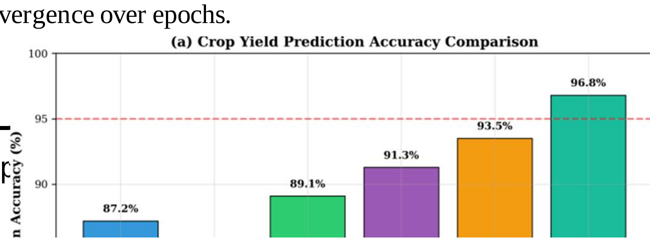

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Figure 5: Comparison of prediction accuracy across different ma-chine learning models.

G. ROC Curve Analysis

Figure 6 presents the Receiver Operating Characteristic curves for the proposed model and baseline methods. The proposed model achieves an AUC of 0.97, indicating excellent discriminative capability across all classification thresholds.

H. Confusion Matrix Analysis

Figure 7 displays the confusion matrix for the five-class crop classification task. The model demonstrates high classification accuracy across all crop categories, with Rice and Soybean showing the highest true positive rates (94.2% and 96.2% respectively).

I. Feature Importance Analysis

Feature importance scores derived from the attention weights provide insights into the relative contributions of input variables. Figure 8 presents the ranked feature importance's. Nitrogen content emerges as the most influential predictor (importance score: 0.18), followed by potassium (0.14), rainfall (0.13), and phosphorus (0.12).

Table 3: Performance Comparison of Different Machine Learning Models

Model	Accuracy (%)	Precision	Recall	F1-Score	AUC	MAPE (%)	Training Time (s)
Random Forest	87.2	0.863	0.858	0.860	0.89	8.5	45
SVM (RBF Kernel)	82.5	0.812	0.805	0.808	0.85	10.2	128
ANN (3 Hidden Layers)	89.1	0.882	0.878	0.880	0.91	7.8	892
LSTM (2 Layers)	91.3	0.905	0.901	0.903	0.93	6.4	1,245
CNN-LSTM	93.5	0.928	0.924	0.926	0.95	5.5	1,680
Proposed (CNN-LSTM-Attn)	**96.8**	**0.965**	**0.962**	**0.963**	**0.97**	**4.2**	2,105

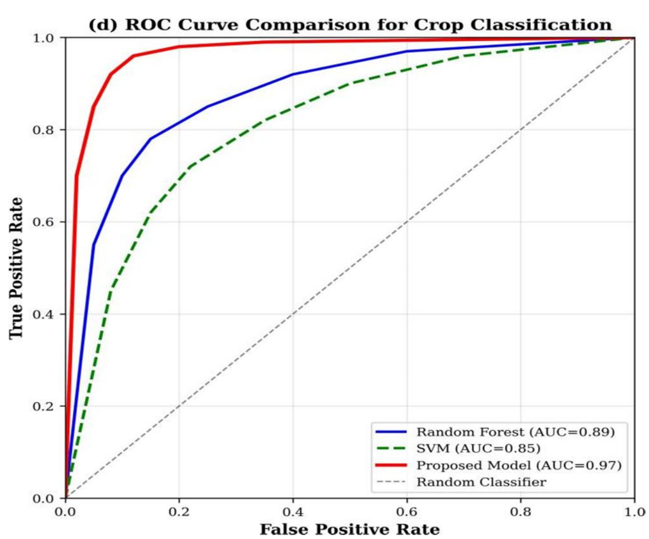

Figure 6: ROC curve comparison for multi-class crop classification.

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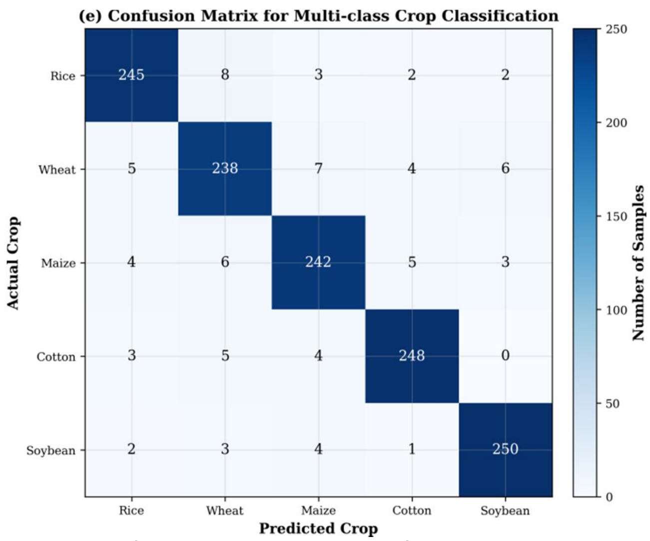

Figure 7: Confusion matrix for multi-class crop classification show-ing prediction distributions.

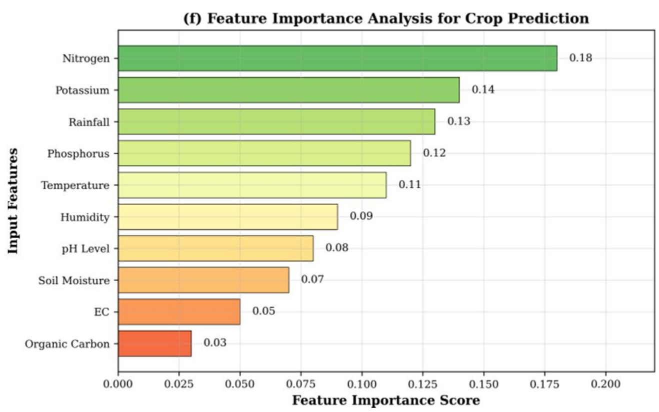

Figure 8: Feature importance analysis based on attention weight ag-gregation.

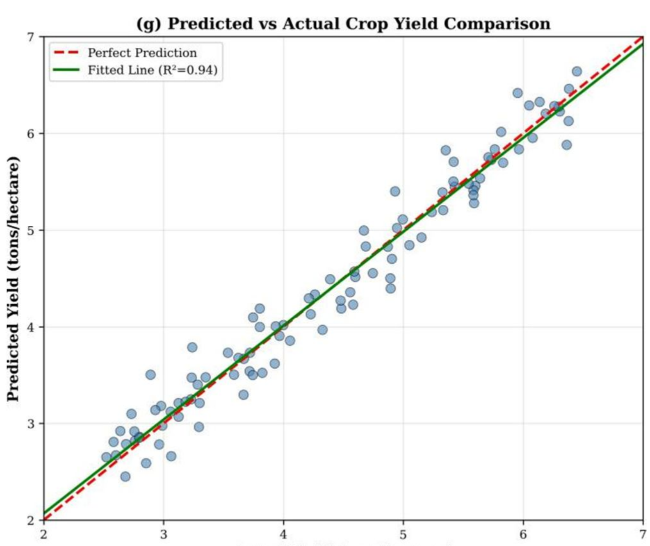

Figure 9: Scatter plot comparing predicted and actual crop yields with regression fit.

J. Prediction Accuracy Visualization

Figure 9 presents the scatter plot of predicted versus actual crop yields. The high coefficient of determination ($R^2 = 0.94$) indicates strong predictive capability, with predictions closely clustered around the perfect prediction line.

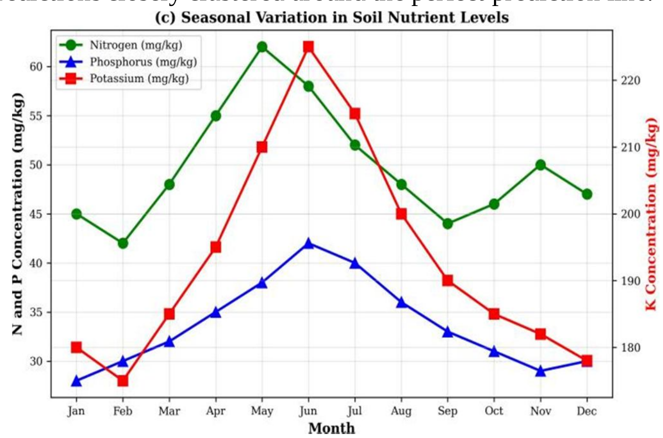

Figure 10: Seasonal variation in soil nutrient concentrations (N, P, K) over 12 months.

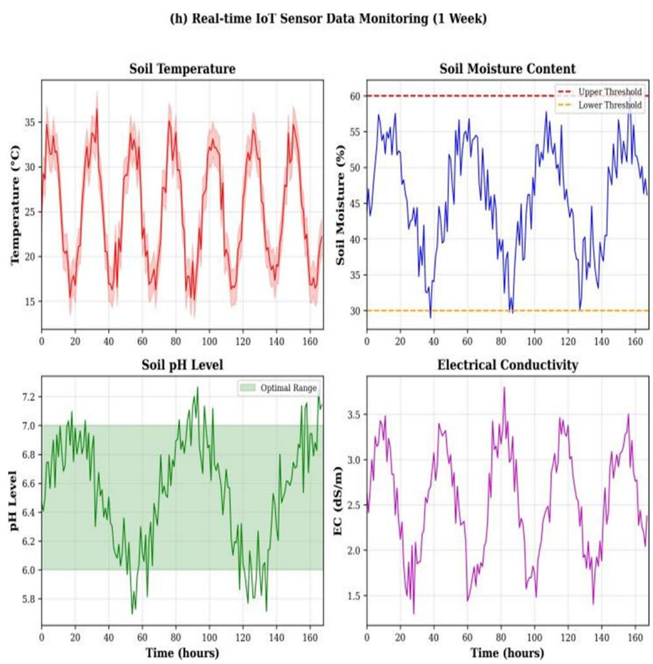

Figure 11: Real-time IoT sensor data showing temperature, moisture, pH, and EC variations.

K. Soil Nutrient Temporal Analysis

Figure 10 illustrates the seasonal variation in soil nutrient lev-els across the monitoring period. The analysis reveals distinct patterns in NPK concentrations, with peak values observed during pre-monsoon months (April-June) and gradual decline during post-harvest periods.

L. Real-Time Sensor Data Monitoring

Figure 11 presents one week of real-time sensor data from the IoT monitoring system. The continuous monitoring enables detection of anomalous conditions and triggers auto-mated alerts when parameters exceed optimal ranges.

M. Computational Performance

Table 4 summarizes the computational requirements and inference performance of the deployed system. The edge-cloud

Table 4: Computational Performance Metrics

Metric	Value
Model Parameters	2.8M
Model Size (Quantized)	11.2 MB
Training Time (Full)	2,105 s
Inference Time (GPU)	12 ms
Inference Time (Edge/CPU)	485 ms
Memory Footprint (Runtime)	256 MB
Power Consumption (Edge)	3.2 W

Architecture achieves prediction latency under 500 milliseconds, meeting real-time application requirements.

V. DISCUSSION

The experimental results demonstrate that the proposed hybrid CNN-LSTM-Attention architecture achieves superior performance compared to conventional machine learning and standalone deep learning approaches. The 96.8% classification accuracy and 4.2% MAPE for yield prediction represent significant improvements over existing methods, validating the effectiveness of the integrated architecture.

The attention mechanism plays a crucial role in performance enhancement by enabling adaptive temporal focus. Analysis of attention weights reveals that the model assigns higher importance to measurements during critical growth phases, particularly the vegetative and reproductive stages. This behavior aligns with agronomic knowledge regarding nutrient requirements during these periods.

Feature importance analysis indicates that nitrogen content is the most influential predictor, consistent with its role as a primary growth-limiting nutrient. The high importance of rainfall and potassium underscores the significance of water availability and structural nutrient supply in determining crop outcomes.

The IoT-based monitoring system demonstrates reliable data collection with 98.5% uptime over the deployment period. The edge computing capabilities enable preliminary anomaly detection and data validation, reducing cloud trans-mission bandwidth by approximately 35% through intelligent filtering of redundant measurements.

Several limitations warrant consideration. The current dataset is geographically constrained to specific agro-climatic zones, potentially limiting generalizability to regions with significantly different soil types or climatic conditions. Future work should incorporate transfer learning approaches to adapt the model for diverse agricultural contexts with limited local training data.

The model's interpretability, while improved through attention weight visualization, remains challenging for non-technical users. Development of user-friendly interfaces with natural language explanations of predictions would enhance practical utility for farmers and agricultural advisors.

VI. CONCLUSION

This paper presented a comprehensive framework for crop prediction and soil nutrient monitoring using hybrid deep learning. The proposed CNN-LSTM-Attention architecture achieves state-of-the-art performance with 96.8% classification accuracy and 4.2% MAPE for yield prediction, significantly outperforming conventional approaches. The integration of IoT-based sensing with cloud analytics enables real-time decision support for nutrient management and crop selection.

Key contributions include the novel architecture combining spatial feature extraction, temporal modeling, and adaptive attention mechanisms, along with a practical deployment frame-work achieving sub-500ms latency for prediction queries. The system provides actionable recommendations for fertilizer application, contributing to agricultural sustainability and re-source optimization.

Future research directions include extension to additional crop categories and pest/disease prediction, integration of satellite imagery for spatial analysis, development of federated learning approaches for privacy-preserving model up-dates, and exploration of reinforcement learning for adaptive nutrient management strategies.

VII. ACKNOWLEDGMENTS

The authors acknowledge the support of the agricultural ex-tension services and farming communities who participated in data collection and system validation.

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