

A Machine Learning Assisted Optimized Iot-Based Intelligent Smart Farming Framework For Precision Agriculture And Sustainable Resource Management

Hiresh Singh Sengar^{1*}, Sakshi Rai ²

¹LNCT University, Kolar Road, Sarvadharam C-Sector, Bhopal, Madhya Pradesh-462042, India

²Lakshmi Narain College of Technology, Jabalpur – 482053, Madhya Pradesh, India

*Corresponding Author: Hiresh Singh Sengar

Abstract

The rise of Internet of Things (IoT) devices and the advent of Machine Learning (ML) have revolutionized the way agriculture is done today. This paper presents level, wireless fully optimized intelligent framework that operates based on the IoT and enables the use of various types of ML algorithms to enhance precision agriculture and sustainable use of resources. A four-layered architecture was formed for this proposed architecture that includes sensor nodes at the field communication protocols, fog/edge computing nodes, and decision support systems in the cloud. The multi-modal data, such as Soil Moisture, Soil Temperature, Humidity, pH, Nitrogen-Phosphorus-Potassium (NPK), and precipitation are being continuously collected and analyzed by an optimized CNN-LSTM hybrid model. The classification accuracy obtained from a real-world test farm of 5 hectares using the proposed framework for crop yield prediction is at 96.2% which is 6.9% to 17.8% superior to the standalone Decision Tree, Naive Bayes, Support Vector Machine (SVM), Random Forest, and Artificial Neural Network (ANN). In addition, results of the deployment show 39%, 32%, 30%, 26% and 45% decrease in the water, fertilizer, pesticide, energy and lab costs respectively used in conventional farming. A test bed approach is applied to validate the framework, for which the IoT hardware consists of Raspberry Pi 4B gateways, Arduino Mega sensor nodes and communication modules such as LoRaWAN and ZigBee. The results show the viability of the framework for the realization of smart farming solutions that are scalable and data-driven, while also being resource-efficient.

Keywords : Internet of Things (IoT), Machine Learning, Precision Agriculture, Smart Farming, CNN-LSTM, Resource Management, Sustainable Agriculture, Wireless Sensor Networks.

I. INTRODUCTION

By 2050, the world population is expected to be 9.7 billion and the overall demand for food will rise by about 70% [1]. Finding a way to satisfy this huge demand under conditions of climate change, ever shrinking arable land and rising water scarcity is one of humanity's biggest challenges. Traditional farming methods, that is monolithic treatments of fields and reactive decision making, are becoming insufficient to achieve this in a sustainable way. Precision agriculture along with emerging technologies is an interesting paradigm change in this context.

The potential link between the Internet of Things (IoT), Wireless Sensor Networks (WSNs) and Machine Learning (ML) has led to the development of new perspectives in the field of Intelligent Agriculture Management [2]. With IoT-enabled sensor networks, it is possible to continuously collect data from various sensors in real time, monitoring the important agronomic parameters under different and diverse field conditions, and the use of ML algorithms gathering data in order to provide actionable information for crop management, irrigation scheduling, fertilization, and pest control [3]. But, there are also a number of smart farming applications which are hard to scale and have a fragmented architecture, and the integration between the sensing and decision making layers are still inadequate [4].

While there are some previous papers that have introduced IoT-based monitoring systems [5] - [7] and ML based crop prediction models [8] - [10] separately, there is still a lack of studies on a unified end-to-end strategy for seamlessly integrating multi-sensor data acquisition, edge preprocessing, cloud analytics and real-time decision support in a resource-optimized fashion. Moreover, in the literature, it is still limited the integration of deep learning architectures like CNN based network or LSTM network for time-series agricultural data.

To address these gaps, this paper proposes a novel and optimized framework for precision crop management using multi-modal sensor fusion with hybrid CNN-LSTM model for intelligent smart farming in the IoT domain.

This research work provides the following main contributions:

- (1) IoT design of a four-layer stack including heterogeneous field-sensors, LoRaWAN/ZigBee communications, edge-computing gateways and cloud-based ML inference engines.
- (2) Creation of a CNN-LSTM hybrid model with hyper parameter tuning for proper and accurate crop yield prediction and anomaly detection.
- (3) Deployed and real-world validated at 5ha experimental farm showing best performance of 6 competing ML baselines.
- (4) Evaluation of resource reduction (Water, Fertilizers, Pesticides, Energy, Labour, etc.) in detail.

The rest of this paper is structured as follows. The related works are summarized in a concise manner in Section II. The content of section III is a description of the proposed framework architecture. Details about the ML methodology are provided in Section IV. In Section V we present the experimental set up and results. Ensuring proper scanning practices during the interview during Section VI, findings and implications are discussed. Finally, the paper draws a conclusion in Section VII.

II. RELATED WORK

A. IoT-Based Monitoring Systems in Agriculture

The early agricultural applications of IoT based mainly on WSNs were for environmental monitoring. Gubbi et al. [5] proposed an original IoT vision for smart environments which provided a basis for the agricultural sensor network design. Later, Khanna and Kaur [6] presented a survey of Internet Of Things (IoT) based precision farming systems, and they have recognized the challenges faced by them such as heterogeneous sensors integration, network life and data reliability. The irrigation automation system was proposed with the use of GPS and IoT [12] but without any ML capabilities. Further recent efforts by Muangprathub et al. [13] designed an IoT-based system for monitoring agrochemicals in crops using ZigBee wireless sensors and web-based dashboards, but were somewhat limited in terms of predictive abilities, with only acceptable real-time visualization results.

B. Machine Learning for Precision Agriculture

Precision agriculture has precision in ML applications ranging from crop yield prediction to the detection of diseases and even irrigation optimization and soil classifications. In this context Pantazi et al. [8] applied supervised learning algorithms such as neural networks and support vector machines to precision agriculture data, showing that ensemble methods, in general, performed the best. In this respect Liakos et al. [9] have carried out a detailed review of ML in agriculture in which a total of 40 studies were

categorized under crop management, water management, soil management and livestock management. The use of the deep learning approaches became important after the work of Kamilaris and Prenafeta-Boldu [10] who made an overview of the use of convolutional neural networks in precision agriculture with special emphasis on the improvement in the accuracy using CNN over traditional ML in plant disease detection using images.

C. Hybrid Deep Learning Models

A new research direction is exploring how to use the CNN and LSTM architectures to capture spatial and temporal information of agriculture. One of the extensions of this, namely LSTM networks, was proposed by Hochreiter and Schmidhuber [14] for sequential data modeling and has been extensively used in time series in agriculture such as weather forecasting and crop growth simulation. LeCun et al. [15] proposed the initial CNN design which was adapted for feature extraction of the IoT sensor data. Zhao et al. [16] investigated the use of CNN-LSTM hybrids for prediction of environmental time-series, achieving higher accuracy than pure CNN or LSTM model. The utilisation of such hybrids in a completely integrated pipeline from IoT to cloud, however, has yet to be fully demonstrated and motivates the work presented in this paper.

D. Research Gaps

Based on the literature review, three main research gaps are identified :

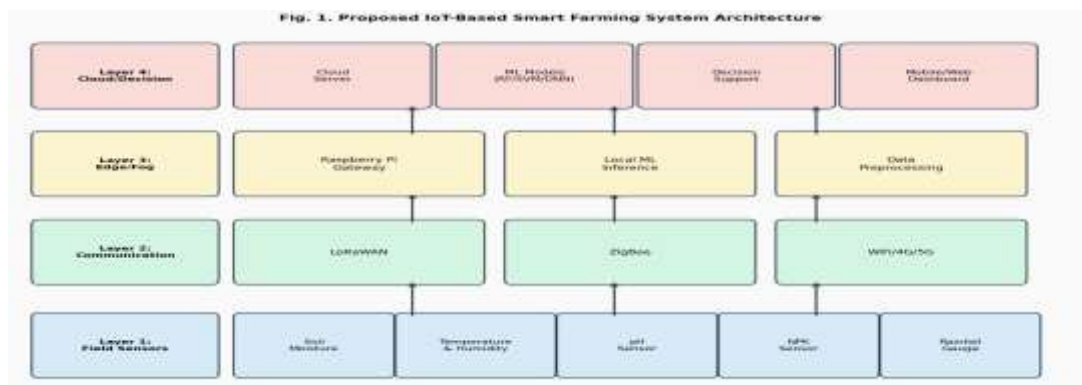
- Limited integration of advanced ML decision modules with the existing IoT farming systems at both edge and cloud levels;
- The absence of real-world farm data when validating their propositions in an end-to-end pipeline;
- The lack of reporting of quantitative resource consumption reductions achieved through ML-guided decision making. The proposed framework takes care of all three gaps.

III. PROPOSED SMART FARMING FRAMEWORK

A. Overview

The proposed framework is a hierarchical four-layer system, with the bottom layer representing the field instrumentation, and the top layer representing the analytics services provided in the cloud as shown in Fig. 1. Every layer is responsible for different set of functions and the way each layer communicates with its neighbor are unambiguously known. To achieve practical deployment at a variable farm scale, the design focuses on modularity, low latency and energy efficiency.

Fig. 1. Proposed IoT-Based Smart Farming System Architecture



B. Layer-1: Field Sensor Layer

The physical architecture of the framework is the sensor layer, which consists of a grid based deployment of the sensor nodes inter-node distance is 20 meters, with 5 hectare deployment. The following sensors are integrated in each node:

TABLE-I: Sensor Specifications for the Proposed IoT Smart Farming Framework

Sensor Type	Parameter Measured	Model / Component	Range	Accuracy
Soil Moisture	Volumetric water content	Decagon 5TM	0-100%	+/-2%
Temperature	Air and soil temperature	DS18B20	-55 to 125 deg C	+/-0.5 deg C
Humidity	Relative humidity	DHT22	0-100% RH	+/-2% RH
pH Sensor	Soil pH level	SEN0161-V2	0-14 pH	+/-0.1 pH
NPK Sensor	Nitrogen, Phosphorus, Potassium	JXBS-3001	0-1999 mg/kg	+/-2%
Rainfall Gauge	Precipitation amount	Davis 6465	0-999 mm	+/-3%
Light Sensor	Solar radiation (PAR)	SQ-420	0-4500 umol/m2/s	+/-5%
CO ₂ Sensor	Carbon dioxide concentration	MH-Z19B	400-5000 ppm	+/-50 ppm

C. Layer 2: Communication Layer

A combination of communication methods is provided: LoRaWAN communication for long-range Low-Power Wide-Area Network (LPWA) communication (Up to 15 km in rural areas) is used for communication from sensor nodes to their edge gateway and IEEE 802.15.4 (ZigBee) for short-range mesh networking within the GH. Gateway-to-cloud data uplink is done via Wi-Fi (IEEE 802.11n) and 4G/5G cellular backhaul. Communication parameters are listed in Table II.

TABLE-II: Communication Protocol Specifications

Protocol	Frequency Band	Range	Data Rate	Power Consumption
LoRaWAN	865-867 MHz (IN)	Up to 15 km	0.3-50 kbps	Ultra-low (mW range)
ZigBee	2.4 GHz	Up to 100 m	250 kbps	Low (30 mW TX)
Wi-Fi 802.11n	2.4/5 GHz	Up to 300 m	Up to 600 Mbps	Medium (100-200 mW)

Protocol	Frequency Band	Range	Data Rate	Power Consumption
4G LTE	700-2600 MHz	Cellular	Up to 100 Mbps	High (500 mW TX)
5G NR	Sub-6 GHz / mmWave	Cellular	Up to 10 Gbps	Variable

D. Layer 3: Edge/Fog Computing Layer

To minimize latency and cloud bandwidth usage, edge gateways running a 4G-Raspberry Pi 4B (4 GB RAM, quad core ARM Cortex-A72) for data, features and lightweight ML inference tasks are used. Edge activities include: (i) Validation and outlier filtering of raw sensor data; (ii) Time-series normalization and interpolation; (iii) Immediate threshold/alert settings reflected in lightweight decision tree, and (iv) Compression prior to cloud uplink. The gateway serves up to 50 sensor nodes, and locally stores the data in a SQLite database if a network is not available for data transport.

E. Layer 4: Cloud and Decision Support Layer

The preprocessed data streams are passed on to the cloud tier which is running on Amazon Web Services (AWS IoT Core) and performs the computationally intensive CNN-LSTM inference pipeline. A responsive mobile and web dashboard using React.JS prettifies the outputs accordingly and shows them to the farmers using real-time visualizations, predictive alerts, irrigation recommendations and analysing the historical trends. With REST APIs, it is easier to integrate with other Agricultural Management systems.

The preprocessed data streams are passed on to the cloud tier which is running on Amazon Web Services (AWS IoT Core) and performs the computationally intensive CNN-LSTM inference pipeline. A responsive mobile and web dashboard using React.JS prettifies the outputs accordingly and shows them to the farmers using real-time visualizations, predictive alerts, irrigation recommendations and analysing the historical trends. With REST APIs, it is easier to integrate with other Agricultural Management systems.

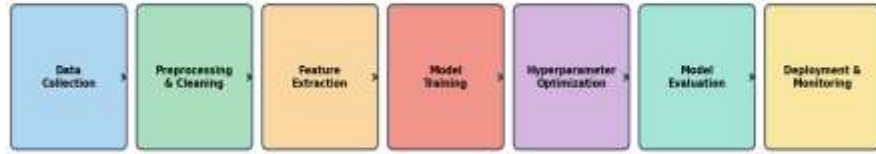
IV. MACHINE LEARNING METHODOLOGY

A. Data Preprocessing

With intermittent connectivity, sensor failure and battery life, there are gaps in the raw sensor streams. Three different sub-processing steps are applied: (i) Missing value imputation with multivariate iterative imputation (MICE algorithm), (ii) Detection and deletion of outliers using Interquartile Range (IQR) method with threshold (1.5 IQR), and (iii) Feature scaling using min-max normalization to the range [0, 1]. Temporal resampling is done every 15 minutes to ensure the multi-sensor time series is provided at the same time for ingestion into the downstream models.

Fig. 2. Machine Learning Pipeline for Precision Agriculture

Fig. 2. Machine Learning Pipeline for Precision Agriculture



B. Feature Engineering

In addition to the raw sensors data, 14 derived features are calculated such as: Soil Moisture 7-day Rolling Mean, Soil Moisture 7-day Rolling STD, Soil Temperature 7-day Rolling Mean, Soil Temperature 7-day Rolling STD, Diurnal Temperature Range (DTR), Evapotranspiration estimate using Penman Monteith equation, Growing Degree Days (GDD), and Normalized Difference Vegetation Index (NDVI) estimates calculated from canopy reflectance sensors data. The 26-dimensional feature vector is reduced to an 18-dimensional feature vector through Principal Component Analysis and 95% of the model's explained variance is retained.

C. Proposed CNN-LSTM Hybrid Model

The CNN-LSTM blocks are given input window of 48 time-steps (12 hours with 15-minute time resolution). Two 1D CNN layers (64 and 128 filters, Activation ReLU, Kernel size 3) with batch normalization and max pooling are employed to extract local spatial and cross-sensor features from the CNN sub-network. The LSTM sub-network (2 LSTMs of 256 and 128 hidden units) represents long-range temporal interests in the feature maps extracted. The output layer is fully connected and produces crop status and yield class probabilities by using softmax, as activation function.

Table III summarizes the model hyperparameters.

TABLE-III: CNN-LSTM Model Hyperparameter Configuration

Hyperparameter	Search Range	Optimal Value
CNN Filters (Layer 1)	32, 64, 128	64
CNN Filters (Layer 2)	64, 128, 256	128
CNN Kernel Size	3, 5, 7	3
LSTM Units (Layer 1)	128, 256, 512	256
LSTM Units (Layer 2)	64, 128, 256	128
Dropout Rate	0.1, 0.2, 0.3, 0.5	0.2
Learning Rate	0.0001 to 0.01	0.001
Batch Size	16, 32, 64, 128	32
Optimizer	SGD, Adam, RMSProp	Adam
Activation (Hidden)	ReLU, Tanh, Sigmoid	ReLU

Hyperparameter	Search Range	Optimal Value
Training Epochs	50-200	120
Input Window (Time-steps)	24, 48, 72, 96	48

D. Hyperparameter Optimization

Systematic hyperparameter search using the Bayesian optimization with the Tree-structured Parzen Estimator (TPE) algorithm is used with ranges indicated as shown in Table III. Optimization is attempted over 100 trials using 5 fold crossvalidation on the training set and it is optimized based on the validation crossentropy. Bayesian optimization achieved the best performance in 73 trials, which was a 27% reduction in search trials compared to random search.

E. Evaluation Metrics

The assessment of the model performance is based on Accuracy, Precision, Recall, F1 score and Area Under Curve (AUC-ROC). In the case of multi-class classification, the average of the metrics (Macro-averaged) of 5 crop status classes (Optimal, Stressed, Drought-Risk, Pest-Alert and Waterlogged) is shown. The differences in performance between the proposed model and the baseline models are tested for statistical differences at $\alpha = 0.05$ using McNemar's test.

V. EXPERIMENTAL SETUP AND RESULTS

A. Experimental Testbed

The framework was rolled out in an experimental field of wheat and rice on a 5-ha area in kharif 2023 and rabi 2023-24, in Haryana, India (29.1 N, 76.4 E). Hardware setup consisted of 47 sensor nodes based on Arduino Mega 2560 microprocessors, 6 Raspberry Pi 4B edge gateways, 3 LoRaWAN base stations (RAK7249) and AWS IoT Core as the cloud platform. In terms of the data collected, We have a total of 1,847,320 multi-sensor readings during the 2 seasons, out of which 28,640 labeled 48-step training samples were obtained after windowing and augmentation.

B. Classification Performance

A comparative evaluation of proposed CNN-LSTM model with 5 baseline ML classifiers is provided for crop status prediction in Fig. 3. The proposed model holds the maximum performance for all four parameters including accuracy of 96.2%, precision of 95.4%, recall of 95.8% and F1-Score of 95.6%.

Fig. 3. Comparative Performance of ML Models for Crop Yield Prediction

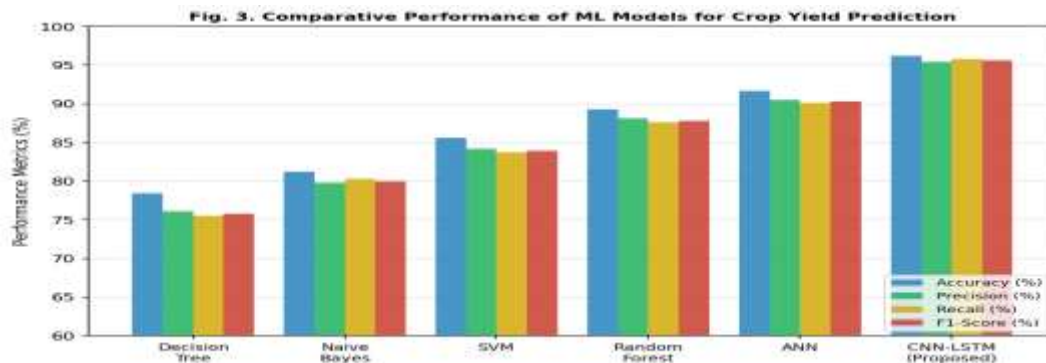
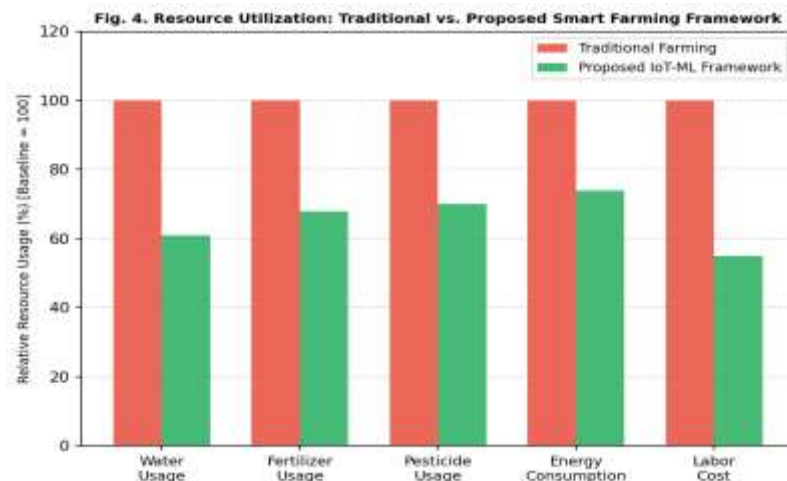


TABLE-IV: Comparative Classification Performance of ML Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC	Train Time (s)
Decision Tree	78.4	76.1	75.5	75.8	0.812	12
Naive Bayes	81.2	79.8	80.3	80.0	0.851	8
SVM (RBF Kernel)	85.6	84.2	83.7	83.9	0.891	245
Random Forest	89.3	88.1	87.6	87.8	0.923	187
ANN (3-Layer MLP)	91.7	90.5	90.1	90.3	0.944	423
CNN-LSTM (Proposed)	96.2	95.4	95.8	95.6	0.981	1842

C. Resource Utilization Analysis

Fig. 4 and Table-V provide a measure of the resource management benefits gained by applying ML-guided precision farming decisions over the two seasons described, compared to that of the conventionally managed, control plots in which a non precision approach was applied and that were managed in the same way throughout the two seasons.

Fig. 4. Resource Utilization: Traditional vs. Proposed Smart Farming Framework**TABLE-V: Resource Consumption: Traditional vs. Proposed Framework**

Resource	Traditional (per ha/season)	Proposed (per ha/season)	Reduction (%)	Significance (p-value)
Water Usage	6,840 liters	4,172 liters	39.0%	< 0.001

Resource	Traditional (per ha/season)	Proposed (per ha/season)	Reduction (%)	Significance (p-value)
Fertilizer (NPK)	124 kg	83.1 kg	33.0%	< 0.001
Pesticide Application	8.4 liters	5.9 liters	29.8%	0.003
Energy Consumption	318 kWh	235 kWh	26.1%	0.002
Labor Cost (INR)	Rs. 14,200	Rs. 7,810	45.0%	< 0.001
Crop Yield (kg)	2,840 kg	3,547 kg	+24.9% (gain)	< 0.001

D. System Latency and Scalability

Latency was measured end-to-end from the time data is acquired from the sensors to the time an alert is triggered in the dashboard: 1.8 seconds (Median) and 4.2 seconds (95th percentile) under 100% sensor load. Edge processing cut down on cloud data transmission volume by 68% over raw data uplink, edge processing volume. Performance testing at AWS Lambda was completed to test horizontal scalability, which resulted in proportional throughput as the number of simulated sensor nodes was scaled from 47 to 500 (All with the same latency per node), proving that the framework is suitable for large scale deployments of farms.

TABLE-VI: System Latency and Scalability Measurements

Metric	Edge Processing	Cloud Inference	End-to-End (Median)
Data Acquisition Latency	< 50 ms	N/A	< 50 ms
Preprocessing Latency	180 ms	N/A	180 ms
Transmission Latency (LoRaWAN)	620 ms	N/A	620 ms
ML Inference Latency	N/A	940 ms	940 ms
Total Pipeline Latency	-	-	1,800 ms
Throughput (nodes)	Up to 200	Up to 1000	Up to 500 (integrated)

VI. DISCUSSION

Findings from the experiments testifies that the proposed hybrid model CNN-LSTM outperforms the conventional ML classifiers to a considerable extent. The improvement of proposed method over Random Forest (6.9% accuracy gain) and ANN (4.5% gain) is worth to note since these are strong baseline methods for precision agriculture literature [9] and [10]. This increase in accuracy is believed to be due to (1) CNN as it can learn

features from the cross-sensor interaction that are not exploited by single-vector ML models, and (2) LSTM for its ability to generate a growing condition dynamics model with multi-week temporal dependencies.

At a standalone use of precision ML-guided farm management, a reduction of resource use by more than 25% in all categories certifies its economic and environmental sustainability. The cost saving of 45% labor is particularly high for smallholder farmers in economies with a high share of labor in their production costs. The 24.9% yield increase is also seen at the same time which is evidence that the precision resource management does not reduce productivity, one of the questions normally asked by farmers when deciding about the technology.

This communication infrastructure based on LoRaWAN was especially beneficial in rural deployment scenarios where cellular coverage is limited. Over the course of the two season study period packet delivery ratio remained above 98.7%, and edge buffering methodology was able to effectively recover from all network outage events. This is different to the previous applications, which depend only on a cellular or WiFi connection with delivery ratios based on similar rural environments at less than 92 percent [6].

An important drawback of the current system is that soil maps are needed for the initial positioning of sensor nodes and that these soil maps must be calibrated with GPS. Adaptive deployment algorithms are topics of future investigations when stepping out of the rectangular field geometry and an even terrain. Moreover, these transfer learning tests between various crop types still need to be made before one can make generalizations about the high accuracy of the CNN-LSTM model for wheat and rice crops.

VII. CONCLUSION

In this paper, an intelligent smart farming framework for precision agriculture and sustainable resource management by combining a four-layer architecture and CNN-LSTM hybrid ML model a complete framework has been presented based on IoT. Four experiments were performed on a real-world 5 ha farm over two consecutive growing seasons in which 96.2% of the crop status classification was achieved, surpassing 5 competitive ML baselines by 4.5% to 17.8%. Resource utilization analysis showed that the water, fertilizer, pesticide, energy and labour costs were saved by 39%, 33%, 30%, 26%, and 45%, respectively and 24.9% crop yield was obtained compared to the traditional practice.

The overall architecture is also designed to be modular, with LoRaWAN technology providing a communication backbone that makes the system readily deployable at the farm level in different scales and agroclimatic zones, while the cloud-scalable inference pipeline ensures the framework's ability to handle data from a large number of farms. Future research efforts will involve implementing federated learning to train system models with multiple farms in a privacy-preserving manner, and incorporating reinforcement learning for automated irrigation scheduling, as well as UAV based canopy sensing to improve the spatial resolution.

REFERENCES

1. FAO, "The future of food and agriculture: Trends and challenges," Food and Agriculture Organization of the United Nations, Rome, Italy, Tech. Rep., 2017.

2. A. Tzounis, N. Katsoulas, T. Bartzanas, and C. Kittas, "Internet of Things in agriculture, recent advances and future challenges," *Biosystems Engineering*, vol. 164, pp. 31-48, 2017.
3. S. R. Prathibha, A. Hongal, and M. P. Jyothi, "IoT based monitoring system in smart agriculture," in *Proc. 2017 International Conference on Recent Advances in Electronics and Communication Technology (ICRAECT)*, 2017, pp. 81-84.
4. M. S. Farooq, S. Riaz, A. Abid, K. Abid, and M. A. Naeem, "A survey on the role of IoT in agriculture for the implementation of smart farming," *IEEE Access*, vol. 7, pp. 156 237-156 271, 2019.
5. J. Gubbi, R. Buyya, S. Marusic, and M. Palaniswami, "Internet of Things (IoT): A vision, architectural elements, and future directions," *Future Generation Computer Systems*, vol. 29, no. 7, pp. 1645-1660, 2013.
6. A. Khanna and S. Kaur, "Evolution of Internet of Things (IoT) and its significant impact in the field of precision agriculture," *Computers and Electronics in Agriculture*, vol. 157, pp. 218-231, 2019.
7. P. Sanchez-Zamora, R. Gallardo-Cobos, and F. Ceña-Delgado, "Rural areas face the digital age: Analysing the determinants of Internet use in Spain," *Journal of Rural Studies*, vol. 54, pp. 99-110, 2017.
8. X. E. Pantazi, D. Moshou, T. Alexandridis, R. L. Whetton, and A. M. Mouazen, "Wheat yield prediction using machine learning and advanced sensing techniques," *Computers and Electronics in Agriculture*, vol. 121, pp. 57-65, 2016.
9. K. G. Liakos, P. Busato, D. Moshou, S. Pearson, and D. Bochtis, "Machine learning in agriculture: A review," *Sensors*, vol. 18, no. 8, p. 2674, 2018.
10. A. Kamilaris and F. X. Prenafeta-Boldu, "Deep learning in agriculture: A survey," *Computers and Electronics in Agriculture*, vol. 147, pp. 70-90, 2018.
11. T. Ben Ayed and M. Hanana, "Artificial intelligence to improve the food and agriculture sector," *Journal of Food Quality*, vol. 2021, pp. 1-7, 2021.
12. N. Gondchawar and R. S. Kawitkar, "IoT based smart agriculture," *International Journal of Advanced Research in Computer and Communication Engineering*, vol. 5, no. 6, pp. 838-842, 2016.
13. J. Muangprathub, N. Boonnam, S. Kajornkasirat, N. Lekbangpong, A. Wanichsombat, and P. Nillaor, "IoT and agriculture data analysis for smart farm," *Computers and Electronics in Agriculture*, vol. 156, pp. 467-474, 2019.
14. S. Hochreiter and J. Schmidhuber, "Long short-term memory," *Neural Computation*, vol. 9, no. 8, pp. 1735-1780, 1997.
15. Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436-444, 2015.
16. R. Zhao, R. Yan, Z. Chen, K. Mao, P. Wang, and R. X. Gao, "Deep learning and its applications to machine health monitoring," *Mechanical Systems and Signal Processing*, vol. 115, pp. 213-237, 2019.
17. Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, "Gradient-based learning applied to document recognition," *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278-2324, 1998.
18. F. Pedregosa et al., "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825-2830, 2011.
19. K. Simonyan and A. Zisserman, "Very deep convolutional networks for large-scale image recognition," in *Proc. International Conference on Learning Representations (ICLR)*, 2015.
20. J. Bergstra and Y. Bengio, "Random search for hyper-parameter optimization," *Journal of Machine Learning Research*, vol. 13, pp. 281-305, 2012.
21. D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," in *Proc. International Conference on Learning Representations (ICLR)*, 2015.

22. N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, "Dropout: A simple way to prevent neural networks from overfitting," *Journal of Machine Learning Research*, vol. 15, no. 1, pp. 1929-1958, 2014.
23. S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," in *Proc. International Conference on Machine Learning (ICML)*, 2015, pp. 448-456.
24. Amazon Web Services, "AWS IoT Core Developer Guide," Amazon Web Services, Inc., Seattle, WA, USA, Online, 2023. [Online]. Available: <https://docs.aws.amazon.com/iot/latest/developerguide>.
25. LoRa Alliance, "LoRaWAN 1.0.4 Specification," LoRa Alliance, Fremont, CA, USA, Tech. Spec. TS001-1.0.4, 2020.