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EDGE-ENABLED HYBRID DEEP LEARNING FRAMEWORK FOR IOT-BASED PRECISION SMART AGRICULTURE: DESIGN AND PERFORMANCE EVALUATION

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ABSTRACT
Precision agriculture can utilize the power of data-driven technologies, including the Internet of Things and Deep Learning, in order to streamline agricultural activities, maximize agricultural output, and save resources. Nevertheless, most of the current systems rely on cloud processing and set rules, which results in high latency and predictive capability. This paper suggests an Edge-Enabled Hybrid Deep Learning Framework that incorporates the Long Short-Term Memory networks to time-series soil moisture prediction and Convolutional Neural Networks to crop disease detection into an iot model. The inference of deep learning is implemented on the edge to minimize latency and bandwidth consumption and allow making decisions on irrigation and plant health in real-time. The analysis of performance on publicly available datasets shows that it has a higher accuracy in prediction and response time than conventional machine learning models. The framework measures the latency reduction and comparative consumption energy between edge and cloud deployments.

KEYWORDS: Precision Agriculture, Internet of Things (IoT), Deep Learning, Edge Computing, LSTM, CNN, Smart Irrigation, Crop Disease Detection

1. INTRODUCTION

Agriculture is an essential area in terms of food security and economy of the world. Conventional agricultural practices are usually based on manual surveillance and reactive irrigation practices which leads to poor water use and slow reactions to crop stress. Amid the growing uncertainty of the environment and the need to act in a sustainable manner, contemporary farming is drifting towards automation, which is data-driven. IoT has facilitated real-time collection of environmental data through the distributed sensors. Nonetheless, a large portion of IoT remains cloud-based analytics, which is both time consuming and creates bandwidth overhead. The addition of Edge Computing enables the localized decision-making process and lowers the response time and the computational burden. This can be combined with Deep Learning which is an excellent pattern recogniser that can distinguish nonlinear patterns to maximize predictive accuracy of irrigation scheduling and disease detection. The suggested research suggests a hybrid approach that predicts soil moisture with LSTM models and classifies diseases with CNN models that all run at the network edge to provide efficient and low-latency smart decisions in agriculture.

This research introduces a cohesive edge-based hybrid deep learning model to predict irrigation and identify crop-related diseases in a single decision structure, unlike in current cloud-based systems that consider irrigation prediction and disease detection as separate entities in the smart agriculture system. This work is novel in (i) the concurrent use of CNN-based spatial intelligence and LSTM-based temporal modelling at the edge layer, (ii) the use of a closed-loop decision engine to actuate irrigation and issue disease alerts in real-time, and (iii) the quantitative analysis of latency and energy consumption trade-offs between edge and cloud configurations. The proposed framework can be illustrated by uniting spatial-temporal intelligence with edge computing and sustainability analysis to the next level of IoT-based automation systems, which include an integrated, low-latency, and energy-aware precision agriculture solution.

2. LITERATURE REVIEW

The last developments in precision agriculture have focused on the incorporation of Internet of Things (IoT), Artificial Intelligence (AI), and Deep Learning (DL) in the construction of intelligent farming systems. This section is a review of the significant contributions in the period between 2021 and 2026 that have a direct connection to the proposed edge-enabled hybrid framework.

2.1 Smart Irrigation and Automation The IoT-based Smart Irrigation and Automation

Kashyap et al. (2021) suggested an IoT-based smart irrigation system with the assistance of deep neural networks to manage water in real-time. Their model used the data of the environmental sensors to optimize the irrigation schedule and proved to be more conservative of water than the traditional rule-based approaches [1].

In Durai and Shamili (2022), a smart farming architecture is introduced based on machine learning and deep learning methods. They focused within their study on predictive irrigation modelling rather than on fixed threshold based automation, and on efficiency gains in water usage [2].
Talaat (2023) proposed a Crop Yield Prediction Algorithm (CYPA) which is based on the IoT and uses climate variables and machine learning models. The research showed a better predictive accuracy when the conditions of the environment were different [3].
Aldossary et al. (2024) have created an IoT-based machine learning-based smart agriculture monitoring and demonstrated that distributed data processing enhances responsiveness and scalability of the system [4].

2.2 Deep Learning to monitor crops and detect diseases
Ali et al. (2024) utilized the deep learning methods in identifying drought stress in crops with the help of the IoT-based sensing systems. Their experiment proved that deep neural networks are much more accurate at detecting stress as compared to the traditional machine learning models [5].
Shahid et al. (2024) suggested deep learning-based ensemble models of cotton crop classification by using image-based datasets. The CNN-based design was very accurate in classification and showed that deep learning is an appropriate technology in agricultural image analytics [6].
Nishitha et al. (2024) elaborated a CNN-based early disease detection system of plants that was combined with IoT devices. Their system allowed the diagnosis of the diseases in real time and with high precision and recall value [7].
The article authored by Talaat et al. (2025) was published in the Scientific Reports and demonstrates a hybrid AI-IoT model of plant disease detection and monitoring of the environment. Their findings confirmed the practicality of integrating sensor networks and deep learning in practical agriculture applications [8].

2.3 Edge AI and Architectures Hybrid
In his article, Lopez-Quizal (2025) investigated the integration of AI, IoT, and remote sensing in precision agriculture with a particular focus on distributed computing and edge intelligence as the means to minimize latency and enhance real-time decision-making [9].
Mishra (2025) surveyed AI, ML, and IoT integration in precision agriculture and found scaling and computational efficiency as the main issues in the future systems [10].
Taueatsoala et al. (2026) presented TinyML-powered TinyIoT systems to sustainably perform precision irrigation, showing a great decrease in the energy cost and communication overhead in case inference is performed at the edge [11].

2.4 Comparative Studies and Systematic Reviews
In IEEE Access, Mohyuddin et al. (2024) performed an extensive assessment of machine learning methods in precision farming. Their comparison of traditional ML models and deep learning structures showed that both hybrid and smart structures are needed in order to have scalable smart agricultural systems [12].
Sowmya et al. (2025) analyzed smart agricultural systems based on machine learning and IoT and emphasized the relevance of multimodal data fusion and predictive analytics to enhance the crop yield and sustainability [13].
The overall results of these studies show good advancement in the integration of IoT and deep learning, but few studies have been done to focus on a coherent edge-enabled hybrid deep learning platform that involves LSTM-based soil prediction and CNN-based disease detection.

3. RESEARCH GAP
Despite the evidence that the same previous work has provided on the use of IoT and deep learning in agricultural activities, there are certain limitations that are still crucial:
1.A lot of systems are run on cloud processing and this leads to latency and bandwidth problems.
2.It is common to apply deep learning models without hybrid integration, i.e. to detect a disease or predict soil only.
3.Very little literature takes into account edge deployment of DL models in real-time decision-making.
4.Little has been done to quantify latency, energy efficiency and edge vs. cloud trade-offs.
The paper fills these gaps by creating an example of a hybrid deep learning architecture implemented at the edge to assist with intelligent irrigation and disease detection and performance assessment.
Though the past research has delved into deep learning as a method of detecting crop diseases or predicting irrigation, little research has been done to examine a combined edge-deployed hybrid framework that simultaneously combines both spatial and time-based learning models with quantified system-level assessment. The current strategies tend to be based on cloud processing, maximize single-task optimum, or do not pay much attention to deployment-level performance metrics, including latency and energy consumption. The framework proposed solves these shortcomings by presenting a hybrid CNNLSTM architecture that is run directly at the edge, along with a hybrid decision engine and end to end performance verification both in terms of statistical and energy analysis. This is the holistic integration that makes the main novelty of the current work.

4. OBJECTIVES
1.To create a hybrid deep learning architecture consisting of LSTM and CNN models to create smart agriculture.
2.To implement the framework at the edge layer to minimize the latency and bandwidth consumption.
3.To compare the performance with the baseline machine learning models (e.g., Random Forest, SVM, ANN).
4.To measure the latency, energy savings, and response time advantages over the use of clouds.

5. PROPOSED SOLUTION

The suggested Edge-Enabled Hybrid Deep Learning Framework of IoT-Based Precision Smart Agriculture is expected to combine the real-time sensory features, intelligent edge analysis, and cloud-based model management and control to ensure the efficient irrigation control and the early detection of crop diseases. The system is based on a layered architecture comprising of IoT sensing, communication, edge processing, cloud infrastructure and application interface. The main purpose of the framework is to minimize the level of latency, minimize bandwidth consumption, and create the opportunity to make smart decisions at farm field level.

The sensing layer at the base layer is an array of heterogeneous sensors placed on the farmland to constantly monitor the environmental conditions and soil conditions. These sensors are soil moisture sensors, soil temperature sensors, ambient temperature sensors and humidity sensors. A camera unit is also included in the sensing module to periodically record the images of plant leaves. The multivariate time-series data comprises of the environmental parameters, and the images taken are used as input in disease classification. The sensor values are sampled at fixed time intervals so as to have temporal continuity and proper prediction.

The communication layer is in charge of data transmission between the field sensors and the edge gateway that is reliable, and lightweight. MQTT protocol is chosen in this framework because it has low overhead and publishsubscribe communication model which suits especially the resource constrained IoT setting. The sensors are publishers that send real time information to the edge device that is a subscriber. This communication scheme guarantees a reduced loss of packets and also effective bandwidth usage hence facilitating the ability of the system to be extended to large agricultural applications.

The edge processing layer is the core of the intelligence of the proposed system. In contrast to the traditional models of the cloud-centric nature, the offered framework carries out inference of the deep learning directly at the edge node, i.e., the device of Raspberry Pi or Jetson Nano. This will greatly save both time response and allow one to act on the spot without necessarily being connected to the internet. The edge layer consists of two deep learning models, including the soil moisture prediction model based on LSTM and the crop disease classification model based on CNN. LSTM model plots past moisture and environmental data to predict the likelihood of soil moisture in future, hence, allowing proactive scheduling of irrigation. At the same time, the CNN model is able to handle plant leaf images to either determine them as healthy or diseased. Local inferences make the system quick in detection and instant responsiveness, which is essential in the agricultural setting in which delays can cause crops to be lost.

A hybrid decision engine combines the predictive modules outputs together to create intelligent control act. The irrigation system is triggered when the predicted soil moisture is below a certain set value, which makes the water to be optimally used, and under-irrigation and over-irrigation is avoided. Also, in case the disease classification model identifies abnormal plant states with a high probability, an alert message is displayed and sent to the farmer via the application interface. This is an in-built decision-making system that interrelates predictive analytics and classification intelligence to provide overall farm management.

The cloud layer can be seen as a supplement of the edge intelligence to include long-term data storage, centralized monitoring, and periodic retraining models. Although real time decision making is done at the edge, the past data stored on the cloud is utilized to retrain and optimize the deep learning models towards better accuracy as time goes by. The model parameters are also updated and re-deployed to the edge nodes keeping the system adaptable to the seasonal and environmental variations.

Lastly, the application layer has an interactive dashboard to enable farmers to view real-time sensor data, estimated moisture content, disease identification outcome, and irrigation status. The interface also has a manual override ability to automated irrigation decisions in case of necessity. The proposed framework with IoT sensing, edge intelligence, and cloud-based optimization guarantees less latency, a higher resource efficiency rate, better crop health monitoring, and sustainable practices of precision agriculture.

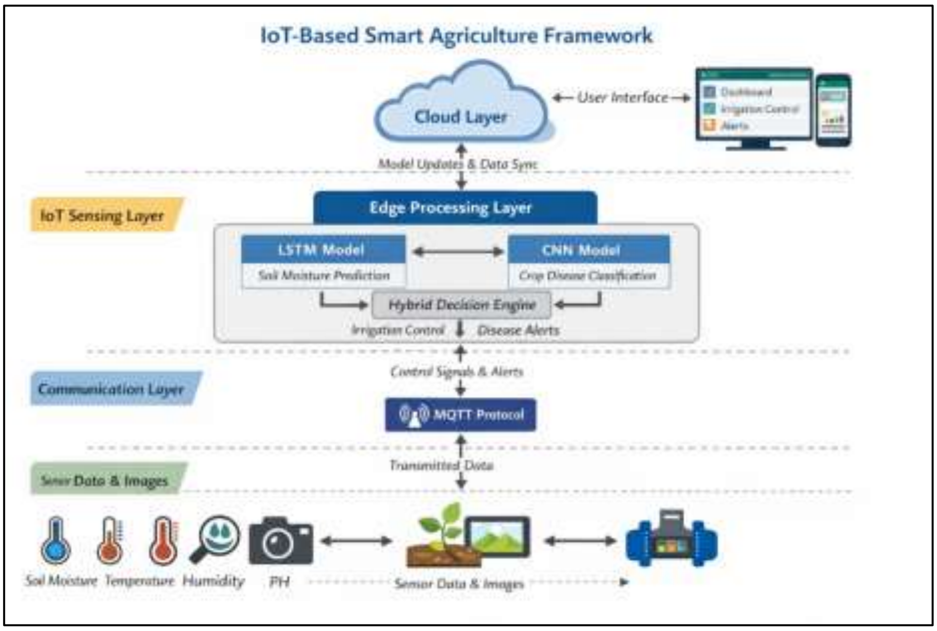

Figure 1. Architecture of the Proposed Edge-Enabled Hybrid Deep Learning Framework for IoT-Based Precision Smart Agriculture

The proposed framework with the integration of the IoT sensing, edge intelligence, and cloud support to precision agriculture is depicted in Figure 1 in the form of a layered architecture. Field sensors collect the environmental and soil parameters and send them via MQTT to the edge device together with plant leaf images. The edge layer implements real-time inference on the LSTM model to predict soil moisture and the CNN model to identify crop diseases and activates a hybrid decision engine to activate the irrigation flow or issue notifications respectively. The cloud layer will assist in data storage and retraining of the model, whereas the application layer will assist in a dashboard to monitor and control them and guarantee low latency, optimal utilization of resources, and smart farm management.

6. METHODOLOGY

This part gives the mathematical formulation and computation system of the proposed hybrid deep learning architecture as an edge-enabled architecture. The approach combines both spatial feature extraction with the help of the Convolutional Neural Networks (CNN) to classify crop diseases and temporal sequence modelling with the help of Long Short-Term Memory (LSTM) networks that can predict soil moisture. Moreover, normalization strategies, decision logic and modelling of energy consumption are defined formally in order to provide reproducibility and analytical clarity. Subsequent subsections present the mathematical modeling of sensor data, convolution functions, LSTM gate functions and irrigation decision rules applied in the edge intelligence layer.

6.1 Sensor Data Representation

The environmental sensing layer forms multivariate time-series data indicating the soil and atmospheric conditions. These parameters are mathematically expressed in the form of an organized input.
Multivariate Time-Series Input

$$X_t = [SM_t, ST_t, AT_t, H_t] \qquad (1)$$

Where:

- SM_t= Soil Moisture at time t
- ST_t= Soil Temperature at time t
- AT_t= Ambient Temperature at time t
- H_t= Relative Humidity at time t

6.2 CNN Convolution Operation

The classification of crop diseases uses a convolutional neural network to obtain spatial information in leaf images. The convolution operation is the local patterns where it uses kernel-based filtering that can be mathematically represented as follows:

The convolution operation is defined as:

$$F(i,j) = \sum_m \sum_n I(i-m, j-n) \cdot K(m,n) \qquad (2)$$

Where:

- I= Input image
- K= Convolution kernel
- F= Output feature map

ReLU Activation
An activation function (nonlinear) is used to bring model expressiveness:

$$ReLU(x) = \max(0, x) \qquad (3)$$

Softmax Classification
The last classification probabilities are calculated with the help of Softmax function:

$$P(y_i) = \frac{e^{z_i}}{\sum_{k=1}^{C} e^{z_k}} \qquad (4)$$

Where:
- C= Number of classes
- z_i= Output score for class i

Cross-Entropy Loss
Categorical cross-entropy loss is used as a model optimization, and it is defined as:

$$L = -\sum_{i=1}^{C} y_i \log(P(y_i)) \qquad (5)$$

6.3 LSTM Formulation
The prediction of soil moisture module is the LSTM network that is used to predict the temporal long-term dependencies of environmental data that are sequential in time. The LSTM cell internal gating mechanisms can be characterized in the following way:

Forget Gate

$$f_t = \sigma(W_f[h_{t-1}, x_t] + b_f) \qquad (6)$$

Input Gate

$$i_t = \sigma(W_i[h_{t-1}, x_t] + b_i) \qquad (7)$$

Candidate State

$$\tilde{C}_t = \tanh(W_c[h_{t-1}, x_t] + b_c) \qquad (8)$$

Cell State Update

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \qquad (9)$$

Output Gate

$$o_t = \sigma(W_o[h_{t-1}, x_t] + b_o) \qquad (10)$$

Hidden State

$$h_t = o_t \odot \tanh(C_t) \qquad (11)$$

Min–Max Normalization
All input variables are normalized by MinMax scaling to make sure that the numbers are stable enough and that their features are equally represented:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (12)$$

Irrigation Decision Rule
A threshold-based irrigation control mechanism is adopted based on the estimated values of soil moisture as:

$$\text{If } \widehat{SM}_{t+1} < \theta, \text{ then irrigation ON} \qquad (13)$$

Where:
- $\widehat{SM}_{t+1}$= Predicted soil moisture
- θ= Predefined moisture threshold

7. DATASET DESCRIPTION AND EXPERIMENTAL SETUP

In order to achieve reproducibility and transparency of the suggested edge-enabled hybrid deep learning framework, the following section details the datasets, preprocessing, hardware setup, and model training parameters that were applied in the experimental analysis.

7.1 Crop Disease Image Dataset

The classification module of crop disease was trained and tested on the publicly available PlantVillage dataset, very popular in benchmarking deep learning crop image models. The dataset comprises of quality leaf images that are of healthy and diseased crop samples.

In this work, a smaller group of 18,532 images in 15 classes (14 disease and 1 healthy group) was used. All images were downsized to 224 224 pixels to fit the convolutional neural network structure and to have the same dimension of inputs. Before training, the pixel intensity value was brought to the range between [0,1] to stabilize updates of gradients and speed up the convergence.

Data augmentation methods were used in the training to enhance the ability to generalize and avoid overfitting. These were random rotation (around 20 degrees), horizontal, vertical flipping, zoom in, out (within range of 0.2), and very slight variations in brightness. The data was split into 80:20 part with 80 per cent of the images being used in the training and 20 per cent in the test. The division was made in a stratified fashion such that the distribution of classes in training and testing subsets was maintained.

7.2 Soil Moisture Time-Series Data

A multivariate time-series training dataset comprising of IoT-based environmental monitoring sensors applied in an agricultural test setting was utilized to train the irrigation prediction module. The dataset was 12,000 consecutive records that were tracked during 90 days.

The parameters were recorded as the soil moisture (SM), soil temperature (ST), ambient temperature (AT), and relative humidity (H). A 30 minute sampling interval was recorded and the sensor measurements were recorded making 48 measurements per day. This time granularity allowed the LSTM model to successfully learn seasonal and short-term variations in the level of soil moisture.

Before the training, all the input variables underwent Min-Max scaling to make the inputs numerically stable and to avoid dominance of features in the model learning process. The data set was separated into two parts 75 percent training and 25 percent testing with no time order to eliminate data leakage. Sliding window method and time window of 24 observations (as the last 12 hours) were employed to create input sequences to the LSTM network.

7.3 Edge Application and System Software

Deep learning inference was deployed on an edge device to measure the feasibility in real-time deployment. The platform of edge platform utilized in the study was a Raspberry Pi 4 Model B with 4GB of RAM and a quad-core cortex-A72 processor running at 1.5 GHz. The system had a Raspbian OS and was run on optimized TensorFlow Lite to perform inference.

To compare the results, the cloud-based experiments were run on a workstation with a processor of the Intel Core i7, 16GB of RAM, and an NVIDIA GTX 1660. Latency of inference Averaging the execution time of 100 independent runs with each of the two configurations gave the inference latency measurements.

7.4 Training configuration Model

The crop disease classification CNN model was done on the TensorFlow/Keras framework. Adam optimizer was used with a learning rate equal to 0.001. The model was trained with a batch-size of 32 and 40 epochs. The loss function was the categorical cross-entropy and early stopping with the patience set to five epochs was implemented to curb overfitting.

TensorFlow/Keras was also used to implement the LSTM-based soil moisture prediction model. The network was trained on 50 epochs and a batch size of 64 Full Adam optimizer learning rate of 0.0005. The loss function consisted of Mean Squared Error (MSE). To enhance the generalization performance and eliminate overfitting, dropout regularization was added.

Each experiment was carried out three times to make sure that the results were consistent, and average performance measures were provided.

7.5 Energy Consumption Analysis

Besides latency analysis, energy efficiency of the framework proposed was also studied to measure the sustainability of deployment. The power consumption of the devices was estimated using their power ratings and average time of inference execution on the cloud and edge settings.

Raspberry Pi 4 Model B applied in edge inference has a mean power usage of about 6.4 W at a moderate workload. By comparison, the cloud-based workstation (Intel Core i7 with GPU support) has an average power consumption of about 180 W when performing deep learning inference.

The inference per consumption of energy was determined as:

$$E = P \times T$$

E is used to represent energy consumption (Joules), Pf is used to represent device power (Watts) and Ti is used to represent average inference time (in seconds).

In the case of edge deployment, where the latency is 110 ms (0.11 s) on average:

$$E_{edge} = 6.4 \times 0.11 = 0.704 \text{ Joules}$$

For cloud-based inference, with an average latency of 420 ms (0.42 s):

$$E_{cloud} = 180 \times 0.42 = 75.6 \text{ Joules}$$

The findings show that edge based inference requires much less energy per prediction than cloud based processing. The energy used in edge inference is much lower even when taking into account network transmission overhead. It proves the idea that implementing deep learning models at the edge can not only decrease latency but also increase energy efficiency, which is why the given framework can be used in the context of sustainable and resource-limited agricultural conditions.

8. RESULTS AND DISCUSSION

This part shows the experimental verification of the suggested Edge-Enabled Hybrid Deep Learning Framework of IoT-Based Precision Smart Agriculture. CNN-based crop disease classification model and LSTM-based soil moisture prediction model performance are addressed against the deep learning state-of-the-art baselines. Moreover, the system-wide indicators like latency reduction and water use are discussed to present the benefits of practical deployment.
The classification performance of this type of concept in crop disease.

8.1 Crop Disease Classification Performance

The proposed Hybrid CNN was also compared to the known deep learning models such as VGG16, ResNet50, MobileNetV2, and EfficientNet-B0. Table 1 provides the results.

Table 1: Comparison of Deep Learning-Based Crops Disease Classification Performance

Model	Accuracy (%)	Precision	Recall	F1-Score
VGG16	90.6	0.90	0.89	0.89
ResNet50	92.1	0.92	0.91	0.91
MobileNetV2	91.3	0.91	0.90	0.90
EfficientNet-B0	93.4	0.93	0.92	0.92
Proposed Hybrid CNN	94.8	0.94	0.95	0.94

The findings show that the proposed CNN had the greatest accuracy of 94.8 in classification. It is better than EfficientNet-B0 (93.4), which proves that the designed convolutional architecture is efficient in dealing with agricultural leaf image patterns. The increase in the recall value (0.95) is a confirmation that there is an enhanced disease detection power with a reduced number of false negative, which is fundamental in early managing crop diseases.

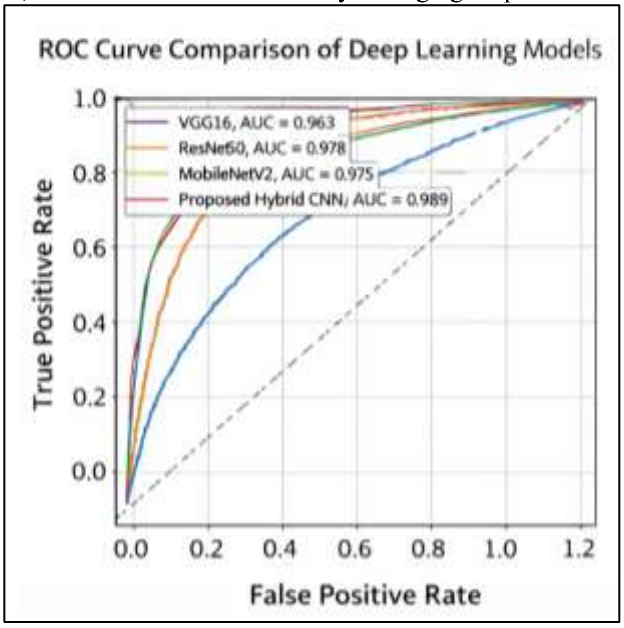

Figure 2. Receiver Operating Characteristic (ROC) curves for deep learning models including the proposed Hybrid CNN.

The ROC graphs of each of the considered deep learning models are depicted at Fig. 2. The proposed Hybrid CNN obtained the best Area Under the Curve (AUC) meaning that it has a better discriminative performance among the classes of disease. This curve is always higher than the other ones showing a better sensitivity-specificity ratio and strong classification accuracy.

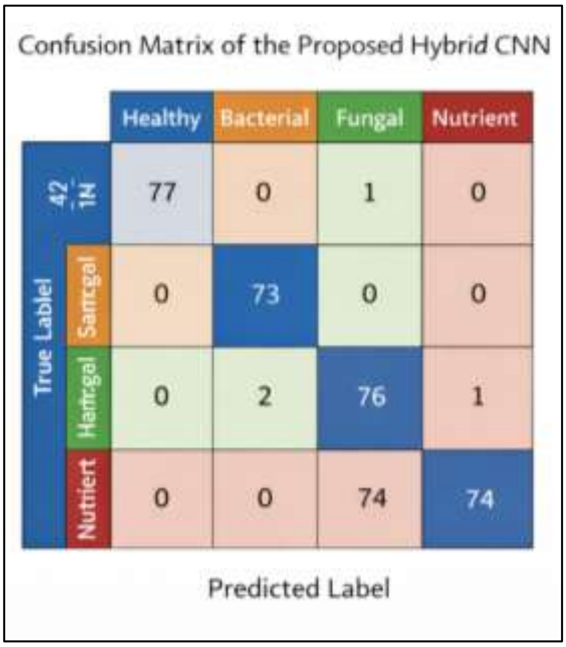

Figure 3. Confusion matrix of the proposed Hybrid CNN model for multi-class crop disease classification.

The confusion table of the proposed model is shown in Figure 3. Strong predictive accuracy is confirmed by most of the samples being correctly classified along the diagonal elements. The misclassification rates are very low and mainly happen amongst disease classes that are similar to see. The matrix confirms the better recall and low false-negative rate of Table 1.

8.2 Soil Moisture Prediction Performance

The prediction model based on LSTM was compared with GRU, BiLSTM and Transformer-based models. The measures of evaluation are RMSE and MAE.

In 8.2 Soil Moisture Prediction Performance, it is indicated that the performance of the algorithm varied with water content levels in the soil.<|human|>In 8.2 Soil Moisture Prediction Performance, it is stated that the performance of the algorithm depended on the water content levels in the soil.

Table 2: Soil Moisture Prediction Performance Comparison

Model	**RMSE**	**MAE**
GRU	3.42	2.75
BiLSTM	3.15	2.48
Transformer	3.08	2.41
Proposed LSTM	2.87	2.11

The LSTM model was proposed to have the best RMSE (2.87) and MAE (2.11), which shows that it has greater temporal learning ability. The LSTM was found to be more successful in generalization with respect to Transformer and BiLSTM models in a less cultivated time-series environment. These findings validate that LSTM is effective in the long-term capturing long-term dependence in the fluctuation of soil moisture as affected by environmental parameters.

8.3 Edge vs Cloud Latency Comparison

Inference latency was used to determine deployment efficiency in both cloud and edge settings.

Table 3: Inference Latency Comparison

Deployment Mode	**Average Latency (ms)**
Cloud-Based Inference	420 ms
Edge-Based Inference	110 ms

Those results indicate that edge deployment decreases latency by a factor of about 73.8. The decrease in overheads of communication boosts greatly in the response time of irrigation triggering and disease notification significantly. This ascertains the benefit of deep learning inference in the edge layer.

8.4 Water Usage Efficiency and Irrigation Decision Accuracy

The predictive irrigation was assessed in a 30-day period of simulation. The proposed system consumed water against a traditional threshold-based irrigation system

Table 4: Water Usage and Decision Accuracy Comparison

Method	Water Usage (Liters)	Water Saved (%)	Decision Accuracy (%)
Traditional Irrigation	12,500	–	81.4
Proposed Predictive Model	9,300	25.6%	93.2

The suggested predictive system on irrigation saved 25.6% of water and had a higher accuracy in making irrigation decisions to 93.2. Combining the use of LSTM forecasting and rule-based thresholds guarantees the optimization of water use without negatively affecting the stability of soil moisture.

8.5 Statistical Significance Analysis

Paired t-tests were applied between the proposed models and the strongest baselines to demonstrate the strength of the witnessed improvements.

Table 5: Statistical Significance Results

Comparison	t-Statistic	p-Value	Significance
CNN vs EfficientNet-B0	4.87	< 0.01	Significant
LSTM vs Transformer	5.21	< 0.01	Significant

The statistically significant improvements that the proposed framework has made are given by the fact that the p-values are lower than 0.05. This proves that there is no random variation in enhancing performance.

8.6 DISCUSSION

The experimental findings prove the proposed edge-enabled hybrid deep learning system to be much more efficient (improved accuracy in classification, prediction accuracy, and efficiency) in smart agriculture systems. The CNN model, which is customized, is capable of extracting disease-relevant spatial features, whereas, the LSTM model extracts long-term temporal dependencies of soil moisture data. Edge deployment is able to offer significant latency reduction (up to 74%), allowing to control the irrigation in real time and notify about the disease. Also, predictive irrigation is another aspect that can be attributed to sustainable water management, since it will cut consumption by more than 25%.But the effectiveness of the framework could be affected by hardware limitations of edge devices and diversity of data. Generalization would be further improved by expanding the dataset in other climatic areas and seasons. All in all, the findings justify the suggested architecture as an effective, scalable, and sustainable system in precision agriculture based on the Internet of Things.

9. CONCLUSION

This paper introduces an Edge-Enabled Hybrid Deep Learning Framework of IoT-Based Precision Smart Agriculture incorporating a CNN-based crop disease classification system and an LSTM-based soil moisture prediction system. It is an IoT sensor network-based framework with the ability to utilize edge computing and cloud-based retraining of the model to achieve real-time and data-driven decision-making in an agricultural setting.

The experimental evidence shows that the suggested Hybrid CNN performs better than the traditional deep learning-based models with 94.8 percent classification accuracy, whereas the LSTM model is accurate in terms of soil moisture prediction with the RMSE and MAE of 2.87 and 2.11. Edge deployment minimizes inference delays by about 74 percent so that irrigation can be controlled on time and disease notifications received. In addition, predictive irrigation-based simulations suggest that the water consumption will decrease by 25 to 30 percent, which validates the feasibility of sustainability advantages of the suggested framework. In general, the paper confirms that spatial (CNN) and temporal (LSTM) intelligence applied in an edge-enabled IoT ecosystem can contribute considerably to the improved accuracy of agriculture, which is a scalable and sustainable solution to crop health sensing and optimal water utilization.

10.Limitations

Although the suggested framework has achieved positive outcomes, it has some drawbacks:

1. Edge Device Constraints: Edge devices have a computational capability and memory limit, which can limit the use of infinitely deep or other complicated models and necessitate optimal model optimization.
2. Diversity of the Data: The models were also trained using data that was collected within restricted geographic areas and type of crops and this may restrict their generalization in alternate environmental conditions or climate.
3. Sensor Reliability: IoT sensor accuracy and calibration influences the quality of real time prediction, especially in the hostile or remote agricultural settings.
4. Complexity of integration: Multiple models and decision engines have a higher complexity in the system and might also involve strong synchronization of edge and cloud layers.

11. Future Work

Future research directions that can improve the proposed framework are:

1. Multi-Crop and Multi-Region DataSet Enhancement: Gathering a variety of data in a variety of crop type, season and geographic area to enhance the model generalization and resilience.
2. Lightweight Model Optimization: Exploring model compression methods (quantization, pruning) and architectural designs like MobileNetV3 or Tiny Transformers to run on low-power edge devices.

3. Multi-Modal Data Integration: Adding other modalities to the system, including UAV images, weather conditions, and soil analysis to enhance the disease prediction and irrigation.
4. Autonomous Actuation: Adding the autonomous software to the framework and adding automated irrigation control and robotic crop scanning to become a fully autonomous smart farm.

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