Enhanced Crop Yield through IoT-Based Soil Monitoring and Machine Learning Analysis for Rice and Sugarcane Cultivation

Original Scientific Paper

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Abstract *– Agriculture, a cornerstone of global economies, faces persistent challenges in efficient crop monitoring. This study introduces a groundbreaking IoT-based framework, integrated with a novel Deep Ensemble Learning (DEL) technique. The cuurent study objective is to enhance rice and sugarcane yield through monitoring soil parameters precisely. The framework employs an array of sensors, including moisture and pH sensors, to determine key soil properties: moisture content, pH level, Nutrient Retention Capability (NRC), and oxygen content. These parameters are crucial in assessing nutrient availability, Organic Carbon Content (OCC), soil texture, and root health. Data captured by sensors is transmitted via an Arduino kit to the cloud, where it undergoes analysis by advanced deep learning models, namely Bidirectional Long Short-Term Memory (Bi-LSTM). The ensemble of models ensures high accuracy in predicting soil parameter. The farmers acquires the processed data through a mobile application that offers actionable insights and facilitating real-time, automated agricultural interventions. Empirical results from field trials demonstrate a significant enhancement in soil parameter detection and monitoring accuracy.The application enables the IoT and DEL-based system in rice and sugarcane fields that enhances the crop yeild by 97% compared to traditional schemes. The study demonstrates the potential of integrating IoT and machine learning in agriculture paradigm shift towards the precision farming, and sets a new standard for sustainable, efficient agricultural practices.*

Keywords*:* *Precision Agriculture, IoT in Farming, Deep Ensemble Learning, Soil Parameter Monitoring, and Crop Yield Optimization*

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AI	Artificial intelligence
Bi-LSTM	Bidirectional Long Short-Term Memory
CSV	Comma-Separated Values
DEL	Deep Ensemble Learning
DL	Deep Learning
GFRC	Global Report on the Food Crisis
GRBF	Generalized Radial Basis Function
GRU	Gated Recurrent Unit
HAR	Human Activity Recognition
HTTP	Hypertext Transfer Protocol
IIS	Intelligent Irrigation System
IoT	Internet of Things
ISNPHC	Integrated Soil Nutrient Prediction and Health Classification
LSTM	Long Short-Term Memory
ML	Machine Learning
NPK	nutrients
NRC	nutrient retention capacity
PPV	Positive Prediction Value
ReLU	Rectified Linear Unit
RNN	Recurrent Neural Network
TAN	Tree Augmented Naïve Bayes
TL	Transfer Learning
TPR	True Positive Rate

1. INTRODUCTION

Agriculture, vital to India's economy, predominantly relying on traditional practices. It serves not only the cornerstone of food production but also as a primary source of income for a large portion of Indian population. The Global Report on the Food Crisis (GFRC) mid-year update of 2023 underscores the alarming state of the global food crisis, emphasising the urgent need for innovation in agricultural practices [1], [2]. Persistent conflicts, economic downturns, and extreme weather events continue to exacerbate global hunger and malnutrition [3]. Conventional agriculture faces several challenges, including heavy reliance on pesticides, high resource consumption, and labor-intensive processes. A significant concern is the inadequate financial returns for farmers. Furthermore, optimal plant growth requires meticulous routines and daily monitoring. Each crop species requires specific management, typically involving manual watering and nutrient application, which is inefficient and laborious [4].

The Technological advancements are gradually addressing limitations through Smart farming, Internet of Things (IoT), artificial intelligence (AI), and robotic machinery to enhance agricultural productivity. However, these innovations can be costly and require specialised knowledge for effective implementation [5, 6]. Precision farming, a critical sector in the agricultural, heavily relies on the integration and transfer of information technology. In this context, IoT plays a vital role by facilitating the transmission of data to farmers[7-9].

The sensor technology has gained prominence in agriculture for real-time data collection, with applications extending to healthcare, military, and telecommunications. In farming, sensors are deployed to monitor soil and environmental conditions that are crucial for crop growth. Soil quality: encompassing soil types and ecosystem characteristics is vital for sustainable plant growth. However, accurately assessing soil quality is complex, and necessitating advanced automatic techniques [10]. The effective farming hinges on a robust system for monitoring soil characteristics. IoT devices are well-suited for this purpose, enhancing various aspects agricultural management [11].

The Key factors for soil condition surveillance include soil temperature and moisture content. Proper balance of these factors aids in determining optimal irrigation schedules. Although watering is not directly correlated with other soil parameters like pH, vitamins, minerals, and salinity levels, these factors remain significant for soil classification [12]. The current research focuses on two major Indian crops, paddy and sugarcane where enhancing yield depends on the effective management of soil parameters. Traditional schemes for monitoring soil parameters have limitations,motivation the adoption of deep ensemble learning for soil parameter classification in this study.

The primary objective is this research is to improve crop growth by optimizing irrigation watering practices and applying nutrients in acordance with real-time field conditions. Thus, to address these challenges, an IoT-based framework is proposed for crop growth monitoring, employing soil parameter analysis. The main contributions of this study are as follows:

- Deployment of soil sensors for crop growth monitoring,and addressing power constraint challenges.
- Extraction of complex soil features using novel Deep Learning (DL) models such as Gated Recurrent Units(GRU) and Bidirectional Long Short Term Memory(Bi-LSTM) networks.
- Adoption of the Bi-LSTM model to effectively capture both past and future temporal dependencies in agricultural time series data.This bidirectional context modelling facilitates accurate interpretation of the dynamic patterns in crop growth, weather varioations, and soil conditions.
- Enhancement of classification performance through an ensemble learning technique that integrating features derived from multiple DL models [13-15].

2. RELATED WORK

The intergation of IoT and Machine Learning (ML) Technologies into agriculture has gained considerable attention in a recent research, with various studies demonstrationg their potential to enhance crop monitoring and yield.

Sharma et al. developed a smart irrigation system for rice cultivation using IoT,and Intelligent Irrigation System (IIS). The system employs soil sensors to continuously monitor soil conditions in rice fields. The sensors data transmitted wirelessly to a web-based database. The databse processes the soil information to determine optimal watering levels and subsequently controls water nozzles through HTTP protocols.The collected data ate stored on a central server and visualized through a interactive dashboard. The key feature of system is an ability to remotely control water pumps based on parameters like soil moisture and flow rate, thereby showcasing the practical applicability of IoT in precision irrigation. [3, 16]

Similarly, Bhushan et al. [16] addressed the challenge of user interfaces in agricultural IoT devices dy designing a low-power remote communication module. This work emphasizes the transition from wired to wireless systems, highlighting to towards more flexible and user-friendly IoT solutions for agriculture. The study furhter anticipates substantial growth in agriculture productivity by 2024 using IoT and wireless sensor networks. This vision is rooted in the ability of IoT to effectively manage soil quality, crop temperature requirements, and irrigation practices [17].

Sahu et al.[3] extended the integrating of IoT in agriculture by incorporating ML for comprehensive crop monitoring. In their approach, wireless sensors collect field data, which is subsequently transformed into CSV format for ML-based processing. The study emphasises the practical deployment of ML modules in agriculture environments and demonstrates how soil parameters and environmental conditions affect plant growth. The application of real-time data within ML models offers valuable insights into climate prediction and the optimization of farming practices, ultimately conserving time, and resources while mitigating crop losses for farmers [18].

Vijayalakshmi et al. explored the application of supervised ML algorithms to classify and map crops based on soil types. The study highlights the efficacy of combining IoT and ML, particularly through ensemble techniques, to achieve precise crop type selection. Thereby, contributing to enhanced agricultural yield [19]. In related study, Afzaal et al. [20] applied various supervised learning methods to improve potato production in Canada's Atlantic region. While Nishant et al. [21] emphasised the importance of improved stacked extrapolation approaches for generating more accurate crop yield forecasts. The collective studies demonstrate the potential growth of deep learning models to furhter improve accuracy and efficiency in agricultural decison making.

Senapaty et al. [22] delved on the analysis of soil nutrients through IoT enabled framework for precision farming. Their framework encompasses multiple stages including data acquision through IoT sensors, preserving real-time data on cloud platforms, accessing data through an Android application, data preparation and subsequent analysis leveraging diverse computational techniques [22]. This approach not only contributes to enhanced crop yeild but also reduces dependency on chemical fertilizers,reinforcing the critical role of IoT in optimising agricultural productivity.

3. METHODOLOGY

This section provides an overview of smart crop growth monitoring with a focus on soil parameters. In this framework a variety of sensors are deployed in paddy and sugarcane fields to measure key soil parameters such as pH, moisture, temperature, dissolved oxygen content, nitrogen content levels, nutrient retention capacity (NRC), and nutrient availability. The collected sensor data is transmitted to the cloud via an Arduino based interface. Once stored in the cloud, the data is processed and analysed using a Deep Ensemble Learning technique as illustrated in the Fig 1.

The Bi-LSTM network is leverged to extract deeper temporal features from the sensor data. An ensemble learning approach is applied by integrating the features derived from the both models to generate a high-quality feature vector. Thector is subsequently employed for classification,enabling the system to determine whether the filed requires irirgation/water or nutrient suppementation. Based on the classification results, the cloud platform communicates with the Arduino kit, which in turn activates the motor for irrigation ON/OFF control and dispatches signal to a drone for precision nutrient application. The architecture of the proposed crop growth monitoring systeme based on soil parameters is depicted in Fig. 2.

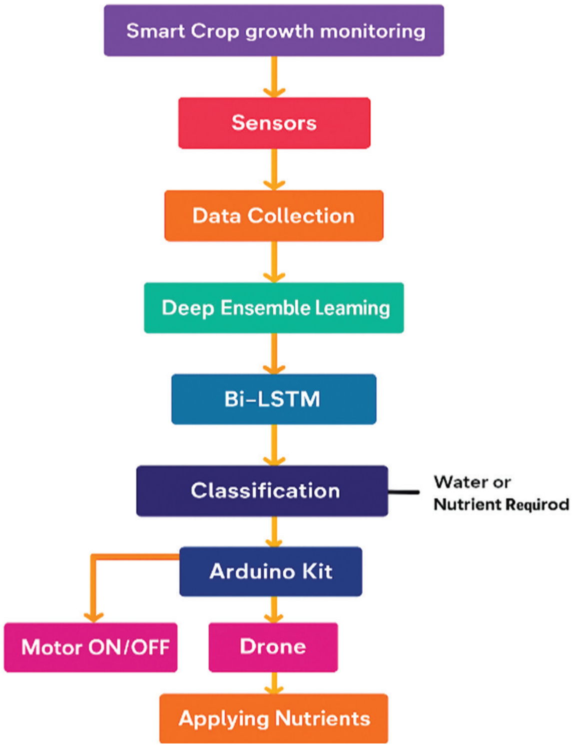

Fig.1. Flow diagram for proposed scheme

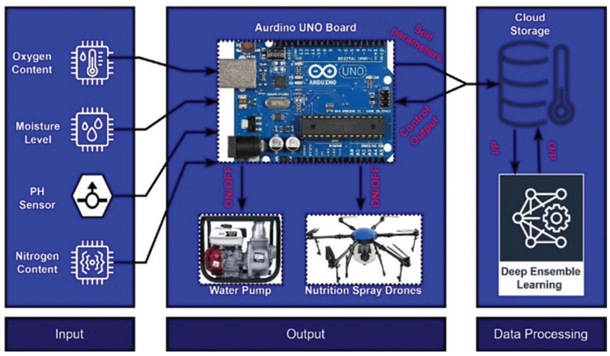

Fig. 2. Overview of the Crop Growth Monitoring System Architecture, Highlighting Soil Parameter-Based Sensing, Data Processing, and Automated Response Mechanisms

A. Data Acquisition Using Soil Sensors

Real-time data are collected from rice and sugarcane fields through the deployemnt of soil sensors. The type of sensors employed for data acquisition are summarized in Table 1 and Table 2. Specifically, an electrochemical sensor is employed to measure the pH value and nutrient content in both paddy and sugarcane fields.

Table 1. Sensors and its Measurements in Paddy Crop Field Monitoring

Soil Parameters	Sensor Used	Ideal Level	Alert Level	Actions/Reasons
PH	PH Sensor	6.0 to 6.7	<6.0 & >6.7	Adjust nutrients if outside ideal range.
Moisture Level	Moisture Sensor	Device reads 270	Device reads 435	Water plants if moisture is high
Oxygen Content	Oxygen Meter	0 to 40%	-	Overwatering lowers soil oxygen, avoid

Table 2. Sensors and its Measurements in Sugarcane Crop Field Monitoring

Soil Parameters	Sensor Used	Ideal Level	Alert Level	Actions/ Reasons
PH	Electrochemical Sensor	5.5 to 6.5	<5.5 & >6.5	Adjust nutrients if outside the ideal range
Moisture Level	Moisture Sensor	80 to 85% (early stage), 50 to 65% (ripening stage)	-	Keep appropriate moisture according to growth stage
Nitrogen Content	NPK Sensor	-	-	Fertilize in a 3:1:2 ratio for healthy crops
Oxygen Content	Soil Oxygen Meter	0.0 to 0.3	0.3 to 0.7	Act if oxygen affects rooting

Soil moisture sensors are employed to measure field humidity and water levels. The oxygen sensors capture dissolved oxygen content in the soil, an essential parameter for effective plant rooting. The soil acidity and alkalinity are determined leveraging a pH sensor, which directly influences microbial activity and micronutrient availability. The pH scale ranges from 0 to 14, with 7 denoting neutrality. The values lower than 5.5 indicate high acidity, values between 5.5 and 6.5 indicte mild acidity, values between 6.5 and 7.5 represent neutrality, values beyond 7.5 reflect slightly alkaline, and values above 8.5 indicate high alkalinity. In addition, the Light Dependent Resistor (LDR) based soil color sensing scheme is leveraged to determine RGB color values which serve as an indirect indicator of soil quality.

The data collection carried out multiple paddy and sugarcane fields in consultation with knowledgeable farmers and agricultural specialists. The topographical map of the region is referenced to account for water availability ensuring somprehensive field coverage. A GPS sensor, integrated with an Arduino UNO board, is employed to determine the latitude and longitude of the field locations enabling spatial tagging of soil data. The informtion combined with sensor measurements is uploaded to cloud storage for further processing.

The communication infrastructure includes a wireless networking module connected to the Arduino board enabling the TCP-enabled internet connectivity facilitating Wi-Fi. The various sensors such as pH,m oisure,electrochemical,temperature and NPK are connected to the Arduino microcontroller board with data aquisituion acheieved through programmed control. The sensor configurations used for data collection are illustrated in the input unit of Fig.1. Once data is acquired and preserved in cloud.Further, the collected data undergoes analysis and classification leveraging an ensemble of Transfer learning (TL) techniquies. This analytical framework facilitates precise assessment of water and nutrient requirements for paddy and sugarcane crops. According to the experiemtnal results actution are triggered automatically wherein drones are deployed for targeted nutrient application and water pumps are controlled for optimized irirgation.

B. Deep Ensemble Learning Method

In this study, a deep ensemble learning method is employed to enhance crop growth monitoring performance. The architecture integrates Bi-LSTM and GRU models. The Bi-LSTM is employed to analyse temporal parameter dependencies in soil data while GRU model focuses on capturing critical soil parameters such as nutrients nutrient levels,pH and moisture content. By combine the predicitive capabilities of both modles the ensemble approach generates high-quality outputs that support precise decision-making for crop growth management.The detailed analysis and netwoek architecture are described in the subsequent subsection.

The soil sensor data uploaded to the cloud undergoes processing throguh a deep learning network. The LSTM based architecture is adopted to address the vanishing gradient commonly encountered in backpropagation. For soil parameter analysis, a multilayer architecture is implemented to ensure robust prediction.The Bi-LSTM model consit of n layers, where the input data are processed sequentially across multiple time steps in both forward and backward directions,thereby capturing past and future contextula dependencies.

The LSTM network operates through three primary gates: the input, forget, and output gate that regulate information flow. Additionally, a candidate gate regulates cell state updates. Their roles are mathematically expressed as in eq. 1 to 4.

$$it=\sigma(W_{t1}ht+W_{t2}ht\text{-}1+B_i) \tag{1}$$

$$ft=\sigma(W_{t1}ht+W_{t2}ht\text{-}1+B_f) \tag{2}$$

$$ot=\sigma(W_{t1}ht+W_{t2}ht\text{-}1+B_0) \tag{3}$$

$$kt=\sigma(W_{t1}ht+W_{t2}ht\text{-}1+B_k) \tag{4}$$

Where, it ,ft , ot , and kt represent the input gate, forget gate, output gate, and candidate gate, respectively. W_{t1} and W_{t2} are the weight parameters of the successive cell in layer n respectively. B_i, B_f, B_0, and B_k are denotes the bias parameters of the input gate, forget gate, output gate, and candidate gate, respectively. The cell state of the LSTM network is defined as follows:

$$Ct=ft.Ct\text{-}1+it.kt \tag{5}$$

In this formulation, the weight parameter and bias parameter of each cell are distributed across all layers of the LSTM network. The Hadamard element-wise operations together with the sigmoid function and the hyperbolic tangent (tanh) activation function regulate information flow and reduce the number of hidden neurons and weight parameters. In this work, the Bi-LSTM processes soil parameters, such as nutrients, pH, moisture, and humidity in both forward and backward directions. The concatenation of forward and backward hidden states are estimated and the outcome is fed into successive layers:

$$h_{t_{fb}}=h_{t_f}.h_{t_b} \tag{6}$$

The Bi-LSTM demonstrates improved capability in modeling sequential dependences through bidirectional processing and it also requires less momory for problem-solving makes this mechanism more efficient sharing compared to conventional deep learnign approaches. Further, to complement Bi- LSTM,the GRU is adopted as the secondary network within ensemble. While RNNs are effective in handling sequential data through hidden state updates.However, RNN suffering from gradient instability over long sequences.

Therefore, GRU simplify the architecture by introducing two gates: reset adn update that regualte memory flow across time steps,thereby capturing both long and short-term depenencies with reduced complexity. The memory in the RNN network is maintained through a hidden state, calculated using the formula:

$$ht=fl(w_1\, h_{t-1}+w_2\, x_t+B) \tag{7}$$

Where, ht is the hidden state of the RNN, x_t is the input data, w_1 and w_2 are the weight parameters of the hidden nodes, and B is the bias parameter. fl is a nonlinear activation function. The current state pt is estimated as:

$$pt=w_p h_t+B_p \tag{8}$$

Bi-LSTM is adept at modelling complex time patterns but is limited by the problems of vanishing and exploding gradients, and its accuracy decreases over longer time durations. Thus, this network was proposed to address these issues, but its extensive training process can be a limitation for real-time applications. In our research, we employ the GRU, a variation of the recurrent neural network.

Both RNN and GRU feature chain-based self-looping units, but GRU's units are more complex. GRU has two gates: update and reset, which regulate the flow of soil data. These gates map soil parameters in the range [0,1], where the number represents the proportion of memory retained. Thus, GRU can handle both long-term and short-term dependencies in time-series data.

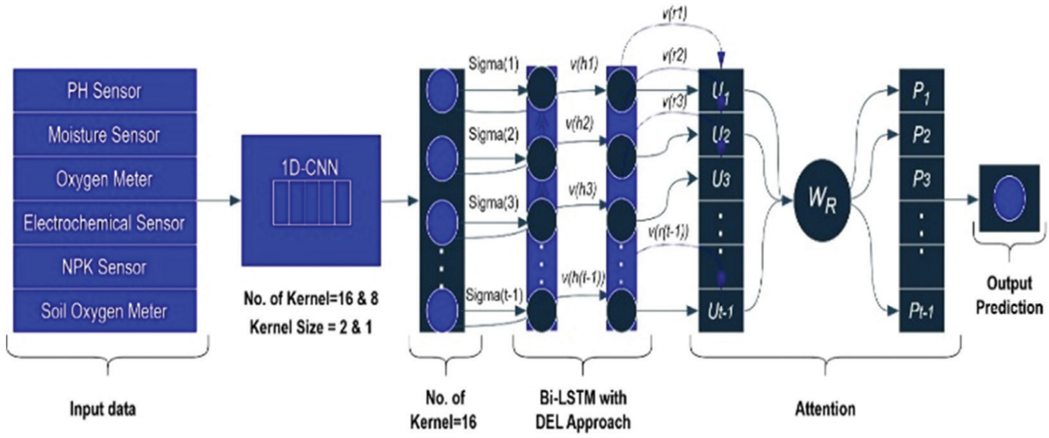

Fig 4. Bi-LSTM structure adapted for DEL method

The GRU's two novel gates, reset and update, are mathematically expressed as follows: The reset gate R_t controls the data transferred from the previous hidden state to the current hidden state:

$$R_t=\sigma(\omega_R\,[h_{t-1}, x_t]+B_R) \tag{9}$$

The memory state m_t is defined using the reset gate and a hyperbolic activation function:

$$mt=tanh(\omega.(R_t.h_{t-1}, x_t)) \tag{10}$$

The update gate U_t localizes which hidden states need updating:

$$U_t=\sigma(\omega_U\,[ht_{-1}, x_t]+B_U) \tag{11}$$

Finally, the hidden state link is generated using both the reset and update gates:

$$h_t=(1-U_t)\, h_{t-1}+U_t\, m_t \tag{12}$$

The output layer of the network generates outputs based on the final hidden state. Depending on the specific task, this output could be a single number, an array of values, or a probability distribution among soil parameter classifications.

The prediction classification outputs of the Bi-LSTM technique and the GRU technique are integrated to enhance soil parameter analysis for better crop growth in cultivation fields. The advantage of using the deep ensemble technique lies in its ability to leverage expertise from multiple classification systems, creating a more robust and effective deep learning model. In this research, the outcomes of two distinct DL models are combined to form a multilayered deep ensemble learning model. As the output of each model corresponds to a single node, these nodes are each connected to a single neuron, activated by the Softmax function using a 3-dimensional vector. A batch normalisation layer is included to improve the precision of the output. Each batch received is processed by this layer, which normalises it using its specific average and standard deviation, then rescales the data using two trainable parameters. Essentially, batch normalisation adjusts its inputs in a coordinated manner. The ReLU activation function is employed in this activation layer to enhance the training speed of the network. The dropout layer serves as a regularisation method that, during training, randomly deactivates a predetermined proportion of neurons within the network. This prevents overfitting and encourages the development of robust and sparse features. It utilises the average and standard deviation of each batch to normalise unit values. This approach can accelerate optimisation by scaling components to a similar scale, irrespective of the network's depth. To further prevent overfitting, it randomly eliminates a set ratio of units from the neural network during training.

4. RESULTS AND DISCUSSION

The soil parameters listed in Tables 1 and 2 are collected from paddy and sugarcane cultivation fields to effectively monitor crop growth. The collected data is pre-processed before being fed into two novel deep learning techniques: the Bi-LSTM network and the GRU network. These dual networks perform a deeper feature analysis of the input data, generating individual classification outputs. To integrate the prediction results of both deep learning networks by employing the Deep Ensemble technique. The classification results of the soil parameter analysis are obtained as single-node outputs from the dropout layer ensuring robustenssnd reduced overfitting.

A. Performance Analysis

Table 3 and Table 4 present the classification outputs of NPK achieved by the proposed DEL technique across various categories. These tables display the maximum prediction accuracy achieved through DEL model. The DEL technique effectively classified soil nutrients into four categories: organic carbon, nitrogen, phosphorus, and potassium for both sugarcane and paddy cultivate fields.

In the paddy field, the classification of the four soil nutrient classes achieved a *Positive Prediction Value (PPV) of 0.8912* and a *True Positive Rate (TPR) of 0.9132*. Additionally, the model attained an overall *accuracy and F1 - of 0.9365 and 0.9736, respectively* that indicates a reliable prediction performance for nutrient classification.

In the sugarcane field, the four nutrient classes are classified with a *PPV of 0.8712 and a TPR of 0.9232*. Furthermore, the accuracy and F1-score for soil nutrient classification in the sugarcane field are approximately *0.9765 and 0.9636, respectively*. The sugarcane cultivate results demonstrates the higher accuracy comapred to paddy field classification with consistently strong precision and recall balance.

Table 3. TPR and PPV content of soil nutrients in the paddy field

Concentration	PPV	TPR	Accuracy	F1 Score
Low	0.865	1	0.986	0.9325
Medium	0.8795	0.832	0.906	0.9625
High	0.8965	0.9012	0.9023	0.9726
Average	0.8912	0.9132	0.9365	0.9736

Table 4. TPR and PPV content of soil nutrients in sugarcane

Concentration	PPV	TPR	Accuracy	F1 Score
Low	0.855	0.5881	0.956	0.9425
Medium	0.8695	0.822	0.966	0.9525
High	0.8765	0.9312	0.9723	0.9626
Average	0.8712	0.9232	0.9765	0.9636

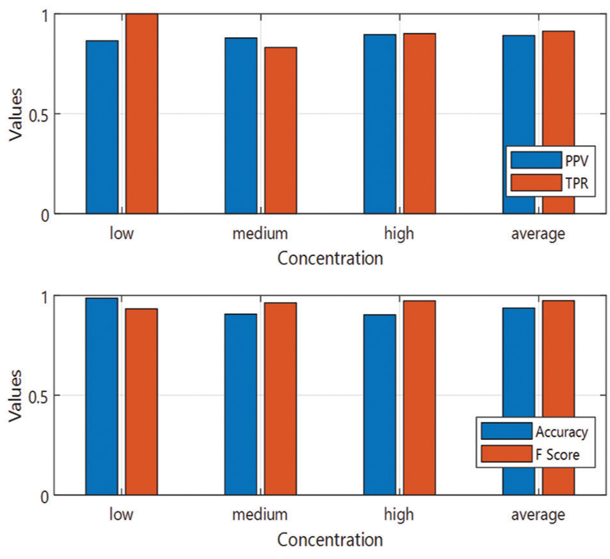

Fig. 4. TPR and PPV content of soil nutrient in paddy field

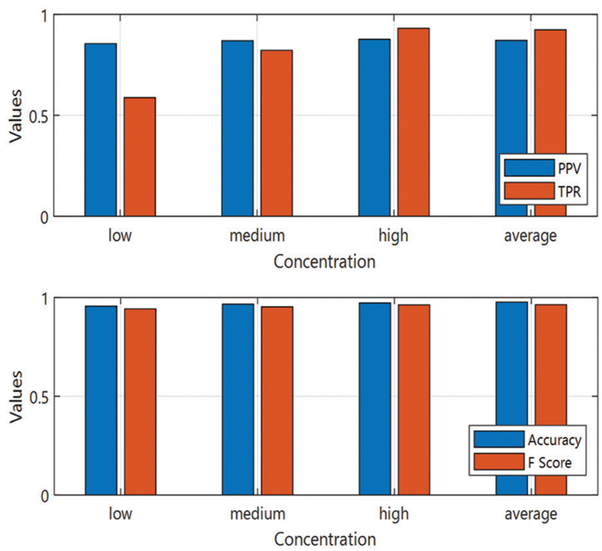

Fig. 5. TPR and PPV content of soil nutrient in sugarcane field

Figs. 4 and 5 illustrate the graphical representations of accuracy and F1-score for soil nutrient classification in both paddy and sugarcane fields. The proposed technique effectively classifies soil nutrients, soil pH, and soil moisture across both paddy and sugarcane fields.

In the paddy field, the classification of organic carbon achieved an accuracy and F1-score of approximately 0.9303 and 0.956, respectively. In the sugarcane field, the corresponding values for organic carbon are approximately 0.9405 and 0.9685, respectively. The results are presented in Table 5 which emphasizes the classifiaction outcomes for soil pararmetes across the paddy and sugarcane fields.

Table 5. Soil Parameter Classification Under Different Classes

Soil Parameters	Paddy		Sugarcane	
	Accuracy	F1-Score	Accuracy	F1-Score
Organic Carbon	0.9303	0.956	0.9405	0.9685
Nitrogen	0.9325	0.9611	0.9625	0.9645
Phosphorous	0.9456	0.9405	0.9524	0.9654
Pottasium	0.9085	0.9125	0.9025	0.9125
Soil PH	0.8725	0.8735	0.8751	0.8574
Moisture	0.8565	0.8567	0.8125	0.8525

For nitrogen classification, the F1-score in both paddy and sugarcane fields is approximately 0.9611 and 0.9645, respectively. In the paddy field, the accuracy of DEL for classifying nitrogen, potassium, and phosphorus concentrations is approximately 0.9456, 0.9025, and 0.8725, respectively. In the sugarcane field, the accuracy and F1-score for soil pH classification are approximately 0.8725 and 0.8735, respectively. Additionally, soil moisture classification achieves an accuracy of approximately 0.8565 in the paddy field and approximately 0.8525 in the sugarcane field. Thus, the performance metrices are illustrated in Fig. 5.

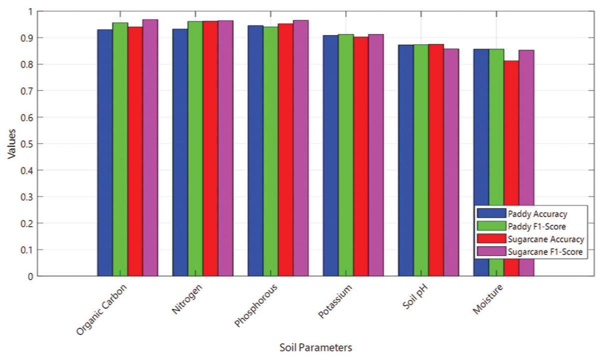

Fig. 6. Soil Parameter Classification under Different Classes

The comparative analysis of the prediction classification results presented in Table 6. The performance of the proposed DEL technique in the context of soil parameter classification. The results build upon the insights discussed earlier in this study. Noteably,the DEL stands out as a remarkable achievement, reaching an impressive 97.5%. which indicates significantly surpasses the performance of traditional DL techniques. This high level of accuracy is critical for precision agriculture where accurate assessment of soil nutrient levels and environmental conditions directly impacts crop health and yeild.

The study also includes four benchmarking techniques for comparison, providing a clear perspective on the state-of-the-art performance of DEL. The results, graphically represented in Fig.6, clearly demonstrate DEL's superiority robustness and reliability over the traditional DL approaches. These findings reinforce the potential of DEL framework as an effective and powerful tool for agricultural research enabling enhanced crop management and decision-making.

Table 6. Comparative Analysis of Soil Parameter Classification Accuracy

Techniques	Nitrogen	Phosphorous	Potassium	Ph	Moisture
ISNPHC	0.9503	0.9412	0.9029	0.8281	0.8752
HAR	0.732	0.8627	0.7584	0.8692	0.8546
GRBF	0.8369	0.9	0.7854	0.8865	0.8185
TAN	0.8125	0.8896	0.7854	0.8695	0.8524
DEL [Proposed]	0.9925	0.9456	0.9085	0.8725	0.8565

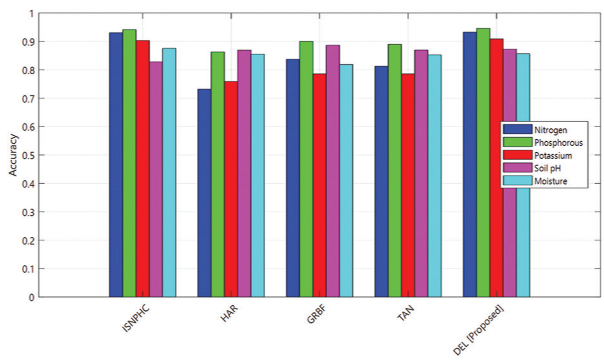

Fig. 7. Comparative Analysis of Soil Parameter Classification Accuracy

A notable aspect of DEL's success is its ability to handle multiple soil parameters including organic carbon, nitrogen, phosphorus, potassium, soil pH, and moisture. The traditional DL models often struggle with multi-parameter classification due to the complexity of the soil data. In contrast, the DEL's deep ensemble approach effectively address these challenges as evidenced by its outstanding performance across all evaluated soil parameters. Furthermore, the results indicate that DEL maintains consistent predictive across different crop fields, including paddy and sugarcane. This versatility suggests that the technique can be applied to a wide range of agricultural contexts, offering valuable insights into soil nutrient levels regardless of the specific crop being cultivated.

5. CONCLUSION

In this research study, a novel DEL technique is designed to classify soil parameters obtained from soil sensors into six distinct categories: soil pH, moisture, nitrogen, phosphorus, potassium, and organic carbon. The DEL technique employs two advanced deep learning models: Bi-LSTM and GRU, to enhance prediction accuracy. To assess the effectiveness of the DEL method, a comprehensive simulation study is conducted using a standardised dataset. The results demonstrate the superior performance of the DEL technique compared to conventional DL methods. Especially, the accuracy values achieved for soil nutrient classification in sugarcane and paddy fields are remarkable, reaching 0.9765 and 0.9365, respectively. The results signifies a substantial improvement in soil parameter prediction.

The demonstrated capabilities of the DEL technique have the potential to rimplication fro real-time agricultureal operations. By leveraging automation this approach can streamline agricultural practices, optimising crop management and resource allocation. However, certain soil parameters like potassium, pH, and moisture, exhibited moderate accuracy that indicating areas for improvement. Future research can focus on refining feature selection and optimising DL architectures and testing the scalability of the DEL technique on larger adn more diverse datasets. Overall, this study emhasizes the potential of DEL as a cutting edge solution for precise soil parameter classification with strong applicability in modern precision agriculture. The outstanding accuracy achieved in our experiments underscores its relevance and promise for improving decision-making in crop management.

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