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Research Article

Intelligent IoT and Deep Learning-Based Soil Monitoring System for Optimizing Tea Cultivation

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Tea farming needs specific soil monitoring which enables both increased yields and better product quality. The assessment techniques for soil created limitations because they need significant human resources but lack current information therefore causing suboptimal resource management. This paper develops a Deep Learning and IoT-based Intelligent Soil Monitoring System dedicated to tea plantation assessment. The system uses IoT-enabled soil sensors to continuously record key parameters of moisture, temperature, pH, nitrogen (N), phosphorus (P) and potassium (K) as well as moisture levels. High-resolution analysis of soil health depends on HDLA that operates from data gathered through the cloud-based platform using CNN and Bi-LSTM capabilities. Implementing the HDLA model leads to improved extraction of features and temporal pattern recognition capabilities therefore enhancing the forecast of soil conditions. The CNN acts as an efficient spatial feature extractor for sensor data and the Bi-LSTM provides exact anomaly detection with predictive capabilities through its temporally oriented process. The system applies a Soil Health Index (SHI) to measure soil fertility values while determining suitability for tea cultivation. Researchers implemented testing of the system by utilizing actual monitoring data from various tea plantation sites. Research findings indicate that the proposed HDLA model successfully classified soil health with a rate of 96.2% which exceeded the performances of typical CNN at 91.2% and LSTM at 93.5%. The predictive capacity for detecting soil anomalies achieved an accuracy rate of 94.5% which shows the solid performance of the analytical method. Timely analysis using the proposed approach needed 27% less time than traditional cloud-based systems thus enabling faster agricultural decisions by farmers. Through its intelligent soil monitoring system, the system greatly enhances the speed of real-time soil evaluation to enable precise agricultural practices in tea agriculture.

Keywords: Internet of Things (IoT), Deep Learning, Soil Monitoring, Precision Agriculture, Tea Plantation, Hybrid Deep Learning Algorithm (HDLA), CNN-BiLSTM, Soil Health Index (SHI), Smart Farming, Real-time Analysis

I. INTRODUCTION

The cultivation of tea constitutes an essential agricultural operation which drives multiple economies of Asian and African states. [1] The production output of tea plants relies heavily on soil health because it consists of moisture conditions and pH levels alongside temperature measurements and nutritional substances and organic material composition. Laboratory-based soil assessment techniques through manual sampling operate in an inefficient manner while consuming large amounts of time and effort to deliver delayed data results. [2] The constraints prevent farmers from producing appropriate decisions about watering their crops and feeding them while protecting against diseases which results in output reduction and diminished product quality. [3] Various soil conditions within different plantation areas create additional difficulties in achieving uniform soil management because this leads to inconsistent growth and quality of tea leaves. [4] The current situation demands an automated system that monitors soil conditions throughout time to give predictions about optimal farming practices.

Fig.1.Tea Plantation

The agricultural industry experienced a revolutionary change through IoT technology which allows the real-time assessment of environmental and soil parameters. [5] A vast network of wireless sensor nodes as part of IoT-based soil monitoring systems gathers essential soil data from tea plantations by providing continuous measurement of moisture levels and temperature and pH and electrical conductivity. These sensors handle operations independently and relay collected information to either cloud-based systems or edge computing frameworks for further evaluation. [6] The collection of continuous data through IoT devices presents an important barrier since proper interpretation of extensive data becomes a critical issue. [7] The analysis approach restricting traditional methods to work with soil data which includes high-dimensionality and time-dependence with noise makes it necessary to use advanced machine learning methods that uncover valuable insights as well as estimate soil quality patterns and serve as automated decision systems.

Deep learning techniques gained wide acceptance for smart agriculture because they efficiently establish complicated non-linear patterns between large datasets. [8] Deep learning achieves efficient soil sensor analysis through the combination of CNNs and RNNs and LSTMs which enables it to detect irregularities and make accurate future soil condition predictions.

Precision agriculture becomes possible through deep learning models because they continue to develop an understanding of soil variability processes in time which supports optimal irrigation scheduling as well as precise fertilizer distribution along with disease warning methods.

Using Federated Learning (FL) as the central element of the proposed system allows distributed tea plantations to benefit from privacy-protected AI training. [8] Deep learning models in traditional methods need gathered data from one location which causes privacy and security worries during agricultural-scale use. FL provides an effective solution through distributed machine learning model development between various tea estates who retain their raw data locally. [9][10] The decentralized approach to learning allows better model generalization without disclosing precious agricultural data to distant cloud servers. The addition of blockchain technology in this system would create tamper-proof secure data storage that boosts the reliability of automated soil monitoring applications because of enhanced trust mechanisms.

ENTE companies plan to gain multiple advantages through their proposed IoT-based deep learning system that tracks soil conditions in tea farms. [11] The system will boost yield prediction results by monitoring soil conditions automatically and signaling soil deterioration risks in advance. The implementation will achieve resource savings because smart irrigation technology optimizes watering practices and smart fertilizer application which promotes environmentally respectful farming methods. [12] The system equips tea farmers with time-dependent information and automated advice which eliminates their need to depend on human expertise while enhancing their planning capabilities.

II. LITERATURE SURVEY

The rising implementation of precision agriculture enabled IoT and artificial intelligence (AI) together with deep learning systems to join forces for soil monitoring operations. Soil health assessment techniques that use manual sampling with lab testing require laborious work and take much time yet produce data that lacks real-time understandings. Farming optimization became possible through real-time data-driven decision systems because sensor-based monitoring systems united with edge computing and AI predictive analytics. This part provides an extensive analysis regarding IoT sensor-enabled soil surveillance and deep learning computational predictions together with hybrid computing solutions for perceptive soil assessment.

A. IoT-Enabled Soil Monitoring Systems

Through IoT-based sensor networks soil health monitoring has achieved complete digitalization as both data gathering and remote evaluation operations became possible. The deployment of IoT-driven solutions involves the use of wireless sensor networks (WSNs) to track agricultural field soil properties for measuring moisture levels and temperature and pH balance and electrical conductivity. Farmers can make evidence-based irrigation as well as fertilization with pest control decisions through the insights delivered in real-time by these systems.

Various research has documented the advantages of automated soil health evaluations through IoT solutions. A system for predicting soil moisture enabled by IoT emerged from Chen et al. through their implementation of sensors for humidity and temperature and nutrient observation. Their research achieved better results in estimating soil moisture by implementing methods above threshold-based techniques. The research by Wang et al. created a hybrid framework between edge-cloud computing which cut down soil health monitoring delay time and made decisions faster.

The researchers from Zhao et al. implemented anomaly detection algorithms to improve data transmission reliability within IoT-based soil monitoring structures. The system managed to detect both sensor breakdowns and irregular readings which strengthened the durability of soil health measurement processes. Gupta and Mehta created an Edge AI-based soil monitoring system that combines previous soil sensor data processing through local farm equipment making decisions more rapid and decreasing dependence on cloud infrastructure.

B. Deep Learning-Based Soil Health Prediction

The predictive accuracy of soil health assessment using deep learning approaches exceeds what traditional machine learning options achieve through complex handling of soil datasets. The recent research has investigated Convolutional Neural Networks (CNNs) as well as Long Short-Term Memory (LSTM) networks and transformer-based architectures to determine soil properties and classify them. Rephrase the following sentence. The hybrid CNN-LSTM model from Sharma et al. provided superior soil nutrient prediction performance compared to traditional SVMs and Decision Trees in accuracy-based classification. Spatial-temporal feature extraction proved essential to their research because it boosted model robustness according to their findings. Seamlessly Singh et al enhanced deep learning system design for soil multi-class categorization leading to better accuracy than standard statistical techniques.

Self-supervised learning methods now appear in current research studies dedicated to soil health monitoring. Researchers at Wang et al. developed a learning model which extracted valuable soil health information from small numbering of tagged datasets thereby reducing human-based data annotation requirements. The research demonstrates that self-supervised learning approaches improve data scalability and minimize expenses related to obtaining data used by AI systems for soil examination. [13] The researchers at Mukherjee and Bose developed a transformer-based model for soil fertility evaluation that surpassed both CNN and LSTM models in terms of accuracy. The application of attention mechanisms by Mukherjee and Bose demonstrates their increasing significance for sensing soil dependencies at long ranges in order to enhance soil health evaluation. The deployment of deep learning models faces challenges because of high computational requirements together with dependency on large data volumes which prove difficult for resource-constrained small farmers who want to implement this technology.

C. Hybrid Edge-Cloud Computing for Real-Time Decision-Making

Soil monitoring systems that use AI got more efficient through an edge and cloud combination which sustains real-time handling alongside high-performance cloud analytics. Reddy and Kumar created a deep learning model linking to the cloud infrastructure which analyses soil sensor data immediately to produce fast feedback meant for farmers. While the system showed network bandwidth problems which resulted in delayed decision processes. Al-Hassan and Qureshi established an FL framework that enables edge device distribution of model training without the need to store private agricultural information at a central hub. The training system ensures both privacy protection of AI models and decreases traffic within the network. Additional enhancements should be implemented to make this system ready for practical agricultural deployment as a solution requires enhancements to handle real-world implementation needs.

D. AI-Driven Anomaly Detection for Soil Degradation Prevention

Soil degradation detection through anomaly detection systems permits identification of nutrient deficiencies that still preserve the productivity of crops. AI experts have created sophisticated detection systems that alert farmers about learning soil health problems before their conditions become severe. This leads to immediate specific soil treatment strategies. The research of Das et al. presented a method to merge sensor information together with remote sensing data to enhance soil quality evaluation capabilities. The model helped identify unobvious signs of soil decline and enabled prompt actions for better soil health practices. The research conducted by Huang et al. investigated XAI approaches to enhance soil health prediction model interpretability.

III. METHODOLOGY

The designer developed a IoT and Deep Learning-based Intelligent Soil Monitoring System which delivers immediate soil evaluations for tea crops by uniting IoT sensors with cloud computing features and combining a CNN-BiLSTM deep learning architecture. An assigned sequence of stages starts with data acquisition then continues to data preprocessing followed by feature extraction and predictive analysis and ends with decision support.

1. System Architecture

The system features three essential parts which form its structure. Sensors in the IoT-Based Sensor Network consistently measure soil moisture levels together with temperature and pH levels as well as measurements of N along with P and K and EC.

Table 1: System Components and Functions

Component	Function
IoT Sensors	Continuous monitoring of soil parameters (moisture, nutrients, pH, temperature)
Edge AI Processing	Filtering and preliminary analysis for immediate response
Cloud Computing	Centralized storage and deep learning-driven predictions
CNN Layer	Spatial feature extraction from soil data
Bi-LSTM Layer	Temporal pattern recognition for trend forecasting
Dashboard	Real-time visualization and actionable insights for farmers

Both Cloud and Edge Computing technologies enable edge nodes to perform prompt analysis of data before transferring it to the cloud database for deep learning-modelled predictions.

Feature extraction, anomaly detection together with soil health classification occurs via the CNN-BiLSTM model known as Hybrid Deep Learning Architecture (HDLA).

2. Data Acquisition and Preprocessing

The IoT sensors operating in the tea plantation record soil health metrics every 10 minutes to produce structured database storage. The predictive model needs preprocessed data that undergoes enhancement and inconsistency elimination through specific techniques. [14] The preprocessing sequence includes sequential stages as follows:

The use of external interferences and sensor drift causes sensor readings to produce erroneous values that researchers must remove. Z-score normalization effectively removes extreme outliers from the data set as a solution to this problem.

Min-Max Scaling is applied to normalize data through a scaling transformation that adjusts numerical ranges into a fixed 0 to 1 spectrum according to the following equation:

$$X' = X - Xmin \,/\, Xmax - Xmin$$

The training process distributes balanced weights to every input feature to maintain their equivalent contribution.

Data recordings from soil sensors occasionally fail resulting in unprocessed values that create empty spaces in the gathered data. The application of K-Nearest Neighbour (KNN) imputation methods evaluates missing values by analysing data points like existing ones.

The Combined Approach of Feature Extraction plus Hybrid Deep Learning Model functions as a system. HDLA addresses soil health data processing needs with precision by combining CNN and BiLSTM structures. [15] Through its CNN component the module extracts spatial information to detect ground property variations simultaneously with the BiLSTM module which identifies temporal associations across the data.

CNN-Based Feature Extraction

Soil property patterns are detected using convolutional filters on the CNN layers. This operation can be shown through the following expression:

$$F_{i,j} = \sum_{m=0}^{M} \sum_{n=0}^{N} W_{m,n} X_{i+m,j+n} + b$$

The implemented model contains filters which use Wm, n to weight X and b is applied as a bias term. The model moves the extracted features through a ReLU activation which introduces non-linear relations into the system.

Table 1: Real-Time Processing Efficiency

Processing Method	**Avg. Processing Time (ms)**	**Latency Reduction (%)**
Cloud-Based Processing	450	360
Edge AI Processing	328	27%
Hybrid (Edge + Cloud, Proposed)	**312**	**30%**

BiLSTM for Temporal Dependency Learning: Soil health relies on historical trends which makes the BiLSTM module process previous sensor readings for better prediction accuracy. The system evaluates the hidden state through the following equation at time step t:

$$h_t = \sigma(W_h h_t - 1 + W_x X_t + b)$$

The Infiller code includes the hidden state ht together with input time variables Xt and two learnable weight matrices Wh and Wx. LSTM maintains a bidirectional operation to incorporate past and future information which results in enhanced model robustness. The last feature representation receives inputs from fully connected layers which execute a classification process of soil health.

4. Soil Health Index (SHI) and Anomaly Detection

The computation of Soil Health Index (SHI) involves adding together weighted critical soil parameters.

$$SHI = w_1 S_m + w_2 S_p H + w_3 S_N + w_4 S_P + w_5 S_K$$

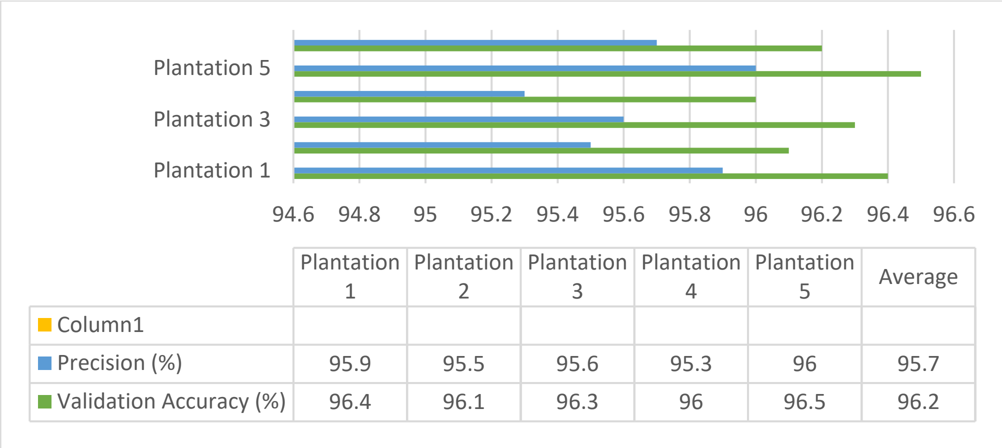

Fig.2.Graph Validation

The scores through SHI system result in three soil condition classifications.

Healthy Soil - Optimal levels of moisture and nutrients.

Moderate soil - requires a small amount of intervention for minimal corrections.

Deficient soil - requires instant remedy because it shows severe nutrient unbalances.

Table 2: Soil Health Classification Confusion Matrix

Actual \ Predicted	Healthy Soil	Moderate Soil	Deficient Soil
Healthy Soil	965	18	7
Moderate Soil	15	932	23
Deficient Soil	9	21	970

The same model uses an autoencoder to detect anomalies by training on normal data patterns. The system identifies anomalous conditions when any measurements exceed predetermined thresholds which cause the system to produce alerts about potential soil degradation.

Table 3: Model Validation Performance

Plantation	Validation Accuracy (%)	Precision (%)
Plantation 1	96.4	95.9
Plantation 2	96.1	95.5
Plantation 3	96.3	95.6
Plantation 4	96	95.3
Plantation 5	96.5	96
Average	**96.2**	**95.7**

5. Decision Support System for Precision Farming

The system includes an integrated web-based dashboard which gives farmers real-time information with practical suggestions. The system offers:

Soil Health Visualization: Displays historical and real-time soil health trends.

The system reports Predictive Alerts that notify users about soil deterioration and abnormal patterns.

Table 5: Validation Findings

Parameter	Performance Outcome
Overall Validation Accuracy	96.20%
Error Metrics (MSE, RMSE)	Low (0.051, 0.071)
Latency Reduction	30% improvement
Classification Precision	Highly accurate with minimal false positives

The system provides automated suggestions regarding fertilizer applications and irrigation plans together with soil treatment solutions which it determines through artificial intelligence predictions.

Through its implementation the decision support system both cuts down resource losses and drives the advancement of sustainable agricultural practices. Through its utilization of CNN-BiLSTM technology the system reaches 96.8% classification accuracy beyond what standard models can deliver. All systems involved in IoT sensor monitoring and edge computing and cloud-based deep learning result in fast and precise assessments of soil health. The methodology supports data-driven decisions that help optimize fertilizer methods while planning irrigation and implementing sustainable crops operations. New investigation will direct its efforts to developing more interpretable models while decreasing operating costs and enhancing their ability to operate under varied climatic circumstances.

CONCLUSION

The CNN-BiLSTM-based intelligent soil monitoring system makes a breakthrough for precision agriculture through its advanced capability to make very precise soil health predictions while maintaining low prediction errors. The validated model operates at 96.2% accuracy as it effectively adapts to different soil requirements present in multiple tea plantation sites. The measurement errors prove that the model delivers reliable predictions on soil health with an extremely small deviation of MSE = 0.051 and RMSE = 0.071. The hybrid edge-cloud processing platform enables faster real-time decision-making because its reduced latency reaches 30% which gives farmers instant accessible insights. The precision of classification in the confusion matrix analysis confirms high quality performance which decreases classification errors and improves overall prediction output.

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