DEEP LEARNING-ENABLED INTERNET OF THINGS SYSTEMS FOR INTELLIGENT SOIL HEALTH MONITORING IN PRECISION AGRICULTURE

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Abstract
The relevance of sustainable agriculture, coupled with challenges posed by climate change, soil degradation and resource mismanagement. At present, the need for intelligent soil health monitoring system has gained increasing significance. Soil health is very critical for productivity of the crops due to influence on nutrient availability, water retention capability, microbial activities and sustainability of the ecosystem. Conventional approaches in soil assessment are based on manual soil sampling and lab analysis, which are extremely laborious, costly and time-consuming, and hence unsuitable for precision agriculture. The emergence of Internet of Things (IoT) technology and Deep Learning (DL) offers new horizons for development of intelligent soil monitoring systems that would continuously collect, analyze and interpret the soil data to support decision making in agriculture. The integration of sensors and deep learning would enable AI-powered soil monitoring systems to monitor the soil conditions such as moisture, temperature, pH, electrical conductivity, and nutrients content and to process huge amounts of data to search for complex patterns and make forecasts about soil conditions and make well-informed decisions in farming. In this research, the whole system of deep learning-based IoT system for intelligent soil health monitoring for precision agriculture has been proposed. The technologies of IoT sensor networks, cloud computing, and data preprocessing techniques, CNN (convolutional neural network) and LSTM (long short-term memory) networks with decision support mechanisms are proposed for the combination.

Keywords: Precision Agriculture, Soil Health Monitoring, Deep Learning, Internet of Things, Convolutional Neural Networks, Long Short-Term Memory.

1. Introduction

The agricultural sector is still one of the key sectors that contributes to the economic development, food security, employment, and environmental sustainability of the world. The world's population is growing at an unprecedented rate to 9.7 billion people by 2050 and the demand for food production is rising as well, making natural resources such as agricultural land subject to unprecedented pressure, particularly soil. Soil is the basis of agricultural productivity as it provides nutrients, controls water availability, supports microbial biodiversity and provides ecological balance. But the excessive use of fertilizers, intensive cultivation, erosion, climate change, and poor management of land resources have seriously lowered productivity of agriculture in many parts of the world due to an increase in soil degradation. These challenges require the creation of intelligent technologies that make continuous evaluation of soil conditions and offer recommendations to increase crop productivity and maintain soil quality, while providing recommendations at the right time.

Most of the traditional soil health monitoring methods involve manually taking soil samples in the field and analyzing them in the lab. These methods enable relatively accurate measurements of soil properties but are costly, labour intensive, time consuming and impractical to continuously monitor large areas of agricultural land. Furthermore, laboratory-based analyses cannot give real-time information that is needed for precision farming applications where taking timely decisions is crucial. The drawbacks of the traditional monitoring technique have led researchers to explore intelligent technologies to facilitate soil data collection, analysis, prediction, and management in an automated fashion.

The advent of the Internet of Things (IoT) has changed the way in which agriculture is monitored. IoT is an interconnected network of sensors that can continually gather data about the environment and soil in agricultural fields. Modern IoT systems incorporate a blend of sensors that are used to measure soil moisture, soil temperature, soil pH, soil EC, nitrogen, phosphorus, potassium, humidity and weather conditions. These sensors use wireless communication technologies like LoRaWAN, ZigBee, Wi-Fi, Bluetooth Low Energy (BLE), NB-IoT and 5G networks to deliver data to cloud platforms where powerful analytical models can analyze data in real-time. As such, IoT has emerged as one of the key pillars of smart agriculture and precision farming solutions.

While there is much data generated from Internet of Things (IoT) devices, traditional machine learning algorithms may have challenges in analysing high complexity, nonlinear, heterogeneous, and time-dependent agricultural data. Deep learning is a promising subfield of AI that can automatically learn hierarchical feature representations from large amounts of data, with minimal manual feature engineering. Deep learning algorithms outperform conventional machine learning techniques by being able to capture spatial, temporal and multidimensional relationships among agricultural sensor data to enhance the accuracy of predictions and decision-making.

A variety of deep learning architectures have been shown to be very successful in agricultural applications. Convolutional Neural Networks (CNNs) have widely been used for spatial feature extraction, classification of images, and identification of soil texture and detection of diseases. The LSTM network was found to be a suitable approach to model the temporal dependency in the sequential soil sensor data and to predict the moisture level and nutrient dynamics, which in turn can be used to predict the need for irrigation. Other architectures, such as Gated Recurrent Units (GRUs), Autoencoders, Transformer networks, Graph Neural Networks (GNNs) and hybrid CNN–LSTM models, are still increasing the potential of smart agricultural monitoring systems. The models are capable of better predictions and can help provide automated decision making in changing environmental conditions.

The combination of IoT and deep learning makes for an extremely smart environment that can revolutionize traditional agriculture, making it a precision farming industry. These systems involve continuous measurement of soil variables by IoT sensors, data handling and processing in the cloud, predictive analysis using deep learning models, and decision support systems that offer guidance to the farmers. The integration helps to manage irrigation, optimise fertiliser use, and detect soil degradation early, enables resource allocation, and promotes sustainable agricultural practices. In addition, the computational power of IoT infrastructures has been further boosted with cloud computing, edge computing, and fog computing technologies, which enable distributed data processing and minimize latency in real-time agricultural applications.

The latest developments of precision agriculture show that more intelligent monitoring systems are being used in developed and developing countries. Digital farming technologies have been a subject of major investments from governments, research institutes and agricultural organisations to enhance food production and minimize environmental footprint. The use of intelligent soil monitoring systems has proven to be highly beneficial in lowering the amount of water used, the amount of fertiliser lost, greenhouse gas emissions, crop yield and improving the overall profit of the farm. These developments are in line with the global sustainability efforts (United Nations Sustainable Development Goals (SDGs)), especially Goal 2 (Zero Hunger), Goal 12 (Responsible Consumption and Production), Goal 13 (Climate Action) and Goal 15 (Life on Land).

Although substantial progress has been made, there are still some research questions that are not addressed. The current soil monitoring systems mainly emphasize the deployment of sensors, but do not make full use of the predictive power of deep learning algorithms. Others use standalone machine learning methods that are not suitable for modelling temporal variation, spatial variability and multimodal sensor data. Further, problems with calibration of the sensors, missing data, communication failure, cyber security, interoperability, scalability, computational cost, and energy efficiency are still significant challenges for a large-scale implementation of intelligent agricultural systems. Also, there are numerous studies that have tested algorithms in a laboratory setting that do not consider the practical problems arising in the field when the algorithms are implemented in actual farming applications.

This study aims to fill these gaps in knowledge by proposing a complete, deep learning based intelligent soil health monitoring framework for precision agriculture using IoT. The proposed approach involves the development of an IoT sensor network, cloud data management, advanced deep learning architectures, predictive analytics, and intelligent decision support systems to enable precise and real-time soil health monitoring. The framework aims to enhance agricultural productivity, sustainable use of resources and the conservation of the environment.

The major contributions of this study include:

- Building an integrated architecture that combines IoT technologies and deep learning models to achieve intelligent soil health tracking.
- Exposing a comprehensive review of the recent advances in deep learning and IoT-based solutions for precision agriculture.
- Identification of the existing research gaps, implementation challenges, and future research directions in intelligent soil monitoring.
- Providing examples of improved irrigation scheduling, nutrient management, and sustainable agriculture decision-making through predictive analytics.
- The ability to support next-generation precision agriculture systems with intelligent automation and real-time decision support in a scalable framework.

2. Related Works

Modern technologies such as Artificial Intelligence (AI), Internet of Things (IoT), cloud computing, and wireless communication have revolutionized precision agriculture by enabling smart farming. Advancements in Artificial Intelligence (AI), Internet of Things (IoT), cloud computing, and wireless communication technologies have transformed precision agriculture into smart farming by enabling intelligent monitoring and data-driven farm management. Among these technologies, one standout combination that holds significant promise is the fusion of deep learning and IoT, which offers solutions to the increasingly complex challenges of soil degradation, unsustainable resource use, and declining agricultural yields. By leveraging deep learning, these algorithms can detect intricate patterns in the data collected by IoT-based sensing devices, make accurate predictions about the state of the soil, and help farmers make informed decisions when it comes to when to plant, when to water, and what to fertilize. The deep learning algorithms can analyse the data gathered by IoT-based sensing devices to identify complex patterns, predict the soil's condition, and assist farmers in making informed decisions regarding plantings, watering, and fertilisation [1][2]. These technologies have combined effectively to pave the way for smart soil health monitoring systems that can enhance irrigation practices, fertilizer use, agricultural yields, and environmental protection.

In recent years, several architectures of IoT, deep learning models, and intelligent decision support systems have been suggested for precision agriculture. This research has focused on various sensing technologies, wireless communication solutions, cloud and edge computing systems, and artificial intelligence algorithms, all aimed at improving soil monitoring and crop management [3] [4]. While much has been done, there is a wide variation between the different studies in the structure of the system, analytical methods, data used, performance metrics, and deployment methods. In addition, various issues such as scalability, interoperability, data quality, computational complexity, cybersecurity, and model interpretability persist that hinder the adoption of intelligent soil health monitoring systems [5][6].

Table 1 presents a summary of selected research that has combined IoT technologies with models based on deep learning for soil health monitoring in precision agriculture. The comparison emphasizes technologies used, the use of deep learning algorithms, key conclusions drawn, and the shortcomings found in prior research.

Table 1. Summary of Recent Studies on Deep Learning-Enabled IoT Systems for Soil Health Monitoring

IoT Technology	DL Model	Study Focus	Major Findings	Identified Limitation
Wireless sensor network	CNN	Soil moisture monitoring	Improved monitoring accuracy and irrigation efficiency	Limited scalability for large farms
IoT and cloud computing	LSTM	Soil moisture prediction	High prediction accuracy for irrigation scheduling	High computational requirements
IoT sensors	CNN–LSTM	Soil nutrient prediction	Better prediction than traditional machine learning	Small experimental dataset
Edge IoT	CNN	Soil classification	Reduced processing delay	Sensor calibration affected performance
Smart sensor network	GRU	Smart irrigation	Improved water-use efficiency	Limited validation under different climates

IoT Technology	DL Model	Study Focus	Major Findings	Identified Limitation
IoT and Edge AI	Hybrid CNN–LSTM	Intelligent soil monitoring	High prediction accuracy	Model interpretability remains limited
Cloud-based IoT	Transformer	Soil property prediction	Superior performance on complex datasets	Computational complexity

2.1 Deep Learning Applications in Precision Agriculture

Deep Learning (DL) is emerging as one of the major methods in artificial intelligence (AI) for precision agriculture. Deep learning models automatically extract features from raw data that are relevant to the problem, which leads to better predictions and classification accuracy, compared to traditional machine learning methods that rely on manual feature extraction. Deep learning has been adopted for a range of agricultural applications such as soil property prediction, crop monitoring, disease detection, yield estimation, and intelligent decision support [2][7]. Within soil health monitoring, deep learning can be used to extract correlations between soil attributes like nutrient concentrations, electrical conductivity, pH, moisture content, and temperature, and make better agricultural management decisions [8][9].

In precision agriculture, several deep learning architectures have been used, such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), and hybrid architectures of CNN–LSTM networks. CNNs are effective at extracting spatial information from agricultural data and have been used in soil classification, remote sensing analysis, and image processing in agriculture [10]. Time-series agricultural data requires models that can capture temporal variations in environmental and soil conditions, which makes LSTM and GRU types of models well suited for analysing these data [11][12]. The hybrid CNN–LSTM models are capable of capturing both spatial and temporal information, which is ideal for forecasting dynamic soil moisture conditions and enhancing irrigation and nutrient management practices [13][14].

While the benefits of deep learning in precision agriculture are significant, several challenges hinder its integration into real-world farming contexts. A large number of high-quality data sets and computational power are usually necessary for training and running deep learning models. Furthermore, the generalisation of models can be impacted by S, C, and F variability across locations [15][16]. The lack of interpretability of deep learning models is a concern, as well, because agricultural stakeholders need transparent and understandable recommendations. In recent years, lightweight deep learning models, explainable artificial intelligence, and edge-based intelligence approaches have received more attention to enhance the efficiency, reliability, and applicability of deep learning-based agricultural systems [17].

Table 2 compares some of the key models used in precision agriculture and soil health monitoring to those based on deep learning.

Table 2. Comparison of Deep Learning Models Applied in Precision Agriculture

Deep Learning Model	Application in Agriculture	Advantages	Limitations	References
Convolutional Neural Network (CNN)	Soil classification, feature extraction, agricultural image analysis	Effective spatial feature learning and high prediction accuracy	Requires large datasets and computational resources	[10]
Long Short-Term Memory (LSTM)	Soil moisture prediction and environmental forecasting	Captures long-term temporal relationships	High computational complexity	[12]
Gated Recurrent Unit (GRU)	Real-time soil monitoring and prediction	Lower complexity and faster training than LSTM	May perform poorly with highly complex patterns	[11]
CNN–LSTM Hybrid Model	Soil health prediction and intelligent monitoring	Combines spatial and temporal feature extraction	Increased model complexity	[13]
Transformer Models	Large-scale agricultural data analysis	Learns long-range dependencies effectively	Requires extensive data and computing resources	[18]

2.2 Deep Learning Applications in Precision Agriculture

Because of its automatic ability to derive meaningful patterns from a vast amount of data, which is often heterogeneous, Deep Learning (DL) is an important technology in modern AI for solving complex problems in precision agriculture. Deep learning models can be trained with the raw agricultural data to learn complex relations without the need for manual feature selection, and thus can be used for soil parameter analysis, environmental conditions, and crop-related information [19]. Soil health monitoring uses deep learning to build soil models, optimize irrigation management, identify nutrient deficiency, and enable intelligent agricultural decision-making based on data collected by IoT sensors and others [7][20].

DNNs such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, Gated Recurrent Units (GRUs), and hybrid CNN–LSTM networks are the architectures that have been explored for agricultural uses. CNNs are good at learning spatiotemporal characteristics from complex data and have been applied in various fields such as soil classification, remote sensing analysis, and agricultural image processing [21]. time series agricultural data, LSTM and GRU models are well suited to overcome the temporal dependency of variables like changes in soil moisture, soil temperature, and nutrient levels proved that LSTM networks have better performance in soil moisture prediction [22], [23], [24] found that CNN–LSTM hybrid networks outperform

LSTM networks and CNN models by integrating their spatial and temporal feature extraction abilities.
Although deep learning models have shown great promise, there are still some challenges to be addressed in applying them to soil health monitoring. Existing models are limited in their use in resource-poor settings, such as in agriculture, because they require high quality and large datasets, and considerable computational resources [25]. Moreover, the interpretability of deep learning models is also an issue, as farmers need farmer-friendly recommendations rather than complicated predictions. In recent years, therefore, there has been a focus on lightweight deep learning models, edge intelligence, and explainable artificial intelligence (XAI) methods to enhance the feasibility, explainability, and scalability of deep learning applications within the agricultural domain [26], [27].

Table 3 shows how traditional monitoring systems for IoT have evolved to become intelligent DL-IoT systems with predictive analysis and automatic decision support. While early implementations of IoT emphasised data collection and monitoring the environment, modern systems incorporate deep learning algorithms to enhance prediction precision and derive valuable insights from intricate agricultural data.

Table 3. Comparison of Deep Learning Models Applied in Soil Health Monitoring

Model	Application	Strength	Limitation	Reference
CNN	Soil classification and feature extraction	Effective spatial feature learning	Required large datasets	[21]
LSTM	Soil moisture and environmental prediction	Captures temporal relationships	High computational cost	[22]
GRU	Real-time soil monitoring	Lower complexity than LSTM	Reduced performance for complex patterns	[23]
CNN–LSTM	Soil Prediction and intelligent monitoring	Combines spatial and temporal learning	Increased model complexity	[24]

2.3 Integration of Deep Learning and IoT for Intelligent Soil Health Monitoring

Deep Learning (DL) and Internet of Things (IoT) technologies have created a new paradigm in precision agriculture by leveraging real-time data acquisition with powerful predictive analysis. The IoT systems allow for real-time data collection of soil and environmental conditions using sensor networks, while deep learning models can identify complex patterns and predict future soil conditions. This integration empowers agricultural systems to go beyond conventional monitoring methods and offers intelligent suggestions for irrigation scheduling, nutrient management, and soil quality enhancement [28], [29]. Through the analysis of vast amounts of sensor-generated data, DL–IoT systems can aid in making informed decisions and optimizing agricultural operations.

Recently, soil health monitoring has been studied with the help of an integrated DL–IoT framework that proved to be effective. In agriculture, IoT sensors are used in fields to measure soil moisture, temperature, pH, and nutrient levels, and deep learning models are used to analyze this data to predict and classify. Hybrid models, such as CNN–LSTM, have recently emerged as a promising approach as they consider both spatial feature extraction and temporal pattern learning, which can help to achieve better performance in predicting dynamic soil conditions

[30], [31]. In addition, the use of cloud computing and edge computing has improved these systems by enabling them to handle large amounts of data and lower latency for real-time agricultural applications [32], [33].

Although significant advances have been made in soil monitoring systems based on DL–IoT technologies, several challenges remain to be addressed. The majority of the existing models are built and tested on limited data from particular sites, limiting their generalizability to different soil conditions, climatic zones, and farming systems [34], [35]. Moreover, issues such as sensor reliability, data security, communication infrastructure, computational demand, and model interpretability remain challenges for large-scale deployment. Hence, intelligent soil monitoring systems need integrated architectures that integrate multi-parameter sensing, advanced deep learning algorithms, edge-cloud computing, and explainable decision-support mechanisms to realize reliable and sustainable precision agriculture [36] [37].

2.4 Emerging Technologies Supporting Intelligent Soil Monitoring

New digital technologies, particularly those emerging, have also improved the capacity of smart soil health monitoring systems by bringing computational efficiency, decision transparency, protection, and scaling. Recent technologies like Edge Artificial Intelligence (Edge AI), Explainable Artificial Intelligence (XAI), Digital Twin technology and Federated Learning have received growing research interest due to their ability to overcome some of the drawbacks of traditional deep learning-based IoT systems. These technologies can be used to create self-contained agricultural platforms capable of on-site analysis, facilitate informed decision-making, and enhance the implementation of precision agriculture solutions [38] [39].

Edge AI is proving to be a pivotal technology for optimizing the efficiency of agricultural systems powered by IoT technology by bringing data closer to where it's created. An edge enabled system does some basic analysis of data locally before sending it to remote cloud-based servers, minimizing delays, bandwidth usage, and reliance on an internet connection. Edge AI can play a role in soil health monitoring for real-time irrigation system control, nutrient management, and early detection of soil health anomalies [40] [41]. However, edge deployment would still present some challenges to optimize deep learning models with limited computational resources, energy requirements, and hardware limitations.

Another area of interest has been the application of Explainable Artificial Intelligence and Digital Twin technologies for enhancing the reliability and usability of smart agricultural systems. By using XAI techniques, farmers and agricultural professionals can gain insights into how AI models reach their recommendations, fostering trust and transparency, and boosting their confidence in the accuracy of the advice. Farmers and agricultural professionals can use XAI techniques to understand the logic behind the AI system's recommendations, promoting trust and transparency and improving confidence in the accuracy of recommendations [42] [43]. The Digital Twin approach can be used to model the soil and create virtual prototypes of the actual field, which can then be used for simulations to test soil management and optimize resource use before conducting field operations [44] [45]. Moreover, Federated Learning offers a privacy-preserving solution by enabling multiple agricultural systems to work together to enhance their deep learning models without sharing their sensitive farm information [46] [47]. The technologies hold great promise, but their use in soil health monitoring systems is underdeveloped, leaving avenues for future research on the secure, explainable, and scalable development of intelligent agricultural systems.

The results in Table 4 highlight the significant role of emerging technologies in addressing challenges in traditional deep learning-based IoT systems. Edge AI enhances responsiveness by minimising reliance on cloud-based computing, XAI tackles the issue of limited interpretability in complex deep learning models, and Federated Learning opens the door to secure collaborative model-building across dispersed agricultural systems.

Table 4. Emerging Technologies for Intelligent Soil Health Monitoring

Technology	Application for Soil Monitoring	Major Contribution	Challenges	References
Edge Artificial Intelligence (Edge AI)	Real-time processing of soil sensor data and local agricultural decision-making	Reduces latency and enables faster responses by processing data near IoT devices	Limited computational resources and energy constraints of edge devices	[41]
Explainable Artificial	Interpretation of deep learning predictions for soil	Improves transparency and user confidence in AI-based decisions	Difficulty explaining complex deep learning models	[42]

Technology	Application for Soil Monitoring	Major Contribution	Challenges	References
Intelligence (XAI)	assessment and farm recommendations			
Digital Twin Technology	Virtual modelling and simulation of agricultural environments	Enables prediction of soil behaviour and evaluation of farming strategies	Requires accurate real-time data and complex modelling approaches	[44]
Federated Learning	Collaborative training in agricultural AI models across distributed farms	Enhances privacy by allowing model training without sharing raw data	Communication overhead and model synchronisation challenges	[47]

2.5 Research Gap and Motivation

The literature analysed reveals that deep learning and IoT technologies have contributed to a wide range of innovations in precision agriculture, ranging from automated data acquisition to intelligent data analysis and decision-making for better agricultural practices. Previous research has demonstrated the ability of IoT-based sensing systems to accurately capture key soil characteristics and the capability of deep learning models for soil state prediction and soil data analysis. The previous studies have demonstrated that the IoT-based sensing system can be used to capture key soil characteristics effectively and that deep learning can have powerful prediction capabilities for the soil state and identify the complex relationships in soil data. Despite these advances, the current research is still scattered, with many studies being conducted on single components of intelligent soil monitoring and not on the development of a complete monitoring system that is interwoven with sensing, analysis, prediction, and decision support within a single system.

Current deep learning based soil monitoring IoT methods have a number of drawbacks. Most of the research focuses on one soil health indicator, such as moisture or temperature, but not multiple soil health indicators like pH, electrical conductivity, or nutrient levels [48]. Moreover, most deep learning models are trained with restricted datasets from specific experimental settings, limiting their generalizability to various geographical regions and soil and climatic conditions (Farooq et al., 2022). Other issues like reliability, data quality, computational load, energy efficiency, cyber security, and model interpretability also persist in the field of large scale deployment of intelligent soil monitoring systems [49][50].

In order to overcome the aforementioned challenges, an integrated deep learning-based IoT system that integrates soil sensor multi-parameter sensing, an advanced predictive model, edge cloud computing, and an intelligent decision-making support mechanism is needed [51]. It should include the ability to precisely measure soil health as well as make recommendations for irrigation management, nutrient optimisation, and sustainable agriculture on the fly.

3. Methodology

In this work, an integrated research approach is adopted to develop an IoT system based on Deep Learning for intelligent soil health monitoring in precision agriculture. The methodology involves collecting data using the Internet of Things (IoT), preprocessing the data, training a deep learning model, and evaluating the system for real-time monitoring and predictive analysis of soil health conditions. The method aims to overcome the limitations of traditional soil testing techniques such as labor-intensive data collection, time-consuming analysis, and batch-wise testing, by facilitating continuous monitoring, automated analysis, and intelligent decision-making.

The methodology proposed is structured into steps, including data acquisition, data preparation, feature extraction, deep learning modelling, integration with IoT, and performance evaluation. In deep learning models, the high quality and representativeness of the data sets are important, thus suitable pre-processing methods are used to increase the quality of the data sets and boost the model performance. The approach is based on the use of sophisticated deep learning algorithms that can identify intricate soil interactions and predict results with high accuracy, enabling informed decision-making in agriculture.

The system architecture is designed based on the layered IoT system, which contains a sensing layer, a communication layer, a processing layer, an intelligence layer and an application layer. In smart agriculture, layered IoT architectures have been increasingly used due to their flexibility, scalability, and efficient management of data exchange and flow among the physical devices and the intelligent applications. The suggested architecture involves embedding IoT sensors into the soil with deep learning analytics to create an intelligent soil monitoring solution for precision agricultural settings.

3.1 Research Design and Framework

Research is carried out in a design science and experimental development fashion in which a design of an intelligent soil monitoring framework is introduced, implemented, and evaluated. The design-oriented research methods are frequently applied to computing and engineering research in which technological solutions are designed and tested with real-world problems. The framework aims to utilize IoT sensing systems and deep learning prediction models to enable continuous assessment of soil and provide intelligent recommendations for agriculture.

The developed system is divided into three chief parts: the data acquisition part, AI part, and the decision support part. The data acquisition is based on sensors, which are connected to the Internet of Things in order to gather soil data, and the artificial intelligence is based on a deep learning algorithm, which processes the gathered data. The decision support component displays the analysed results and soil conditions forecast for making agricultural decisions. The same integrated solutions are used in smart agriculture systems to enhance automation and resource optimisation.

3.2 Data Acquisition and Collection

The data acquisition process is one of the most important steps of the proposed deep learning-based soil health monitoring system with IoT since the quality and diversity of the data collected may directly affect the accuracy and reliability of the prediction model. The study is aimed at the acquisition of soil related parameters that give comprehensive information about soil condition and agricultural productivity. Parameters: Soil moisture, soil temperature, pH, electrical conductivity, N, P, K content. All these parameters are chosen as they are significant for soil fertility, availability of water, and suitability for crop production.

The proposed system utilizes sensors connected to the IoT network and used for continuous data gathering of soil information in agricultural environments. The sensor nodes collect the real-time measurements and send the collected information to the analysis processing unit via appropriate communication technologies. The use of IoT for sensing has benefits over traditional soil assessment methods as it enables frequent measurements, minimizes human effort, and facilitates real-time monitoring of soil conditions that are changing over time. Besides real-time sensor data, historical agricultural datasets can also be integrated to enhance the diversity of the training data and enhance the generalisation ability of the deep learning model.

The dataset compiled includes input variables that represent soil and environmental conditions, and output variables that represent soil health conditions. The collected data is passed through a series of preprocessing steps before it is utilised for the model training process, which helps eliminate inconsistencies, address missing data, and enhance data quality. As deep learning models need adequate and representative datasets to learn complex relationships among input features and prediction results, proper data acquisition and preparation are crucial. Table 5 shows the major soil parameters to be included in the proposed monitoring framework. Past research has found that assessing soil health depends on the synergistic interplay between a series of soil properties, as each property only gives fragmentary information about soil health.

Table 5. Soil Parameters Considered for Intelligent Soil Health Monitoring

Soil Parameter	Measurement Description	Importance in Soil Health Assessment
Soil Moisture	Represents the amount of water present in the soil	Supports irrigation planning and water management by determining soil water availability
Soil Temperature	Measures the thermal condition of the soil environment	Influences seed germination, microbial activities, and nutrient processes
Soil pH	Indicates the acidity or alkalinity level of soil	Determines nutrient availability and crop suitability

Soil Parameter	Measurement Description	Importance in Soil Health Assessment
Electrical Conductivity (EC)	Measures the ability of soil to conduct electrical current	Provides information about soil salinity and nutrient concentration
Nitrogen (N), Phosphorus (P), Potassium (K)	Represents essential soil nutrients required for plant growth	Supports fertiliser management and soil fertility evaluation

3.3 Data Preprocessing and Feature Engineering

Pre-processing of data is undertaken to ensure that the raw data collected from the sensor is suitably formulated for deep learning model development. Agricultural data collected from the Internet of Things (IoT) devices can be noisy, missing, might be measured differently, or have inconsistent scales due to measurement errors and environmental factors. Hence, pre-processing techniques are used to enhance the quality of the data and make sure that the data is appropriate for good training and evaluation of the model [52].

Data Preprocessing includes Data Cleaning, normalisation, and Selection of features. Inaccurate or abnormal sensor reading data are removed by data cleaning, and missing values are filled in with proper imputation methods. Normalisation is used to convert the numbers into a common scale so that the parameters with greater value do not dominate the learning process. Feature engineering is performed to determine which soil properties are most correlated to soil health and would be of most benefit to predict soil health.

The data prepared is split into training, validation, and testing sets for building the model and for an unbiased assessment of the model performance. The training, validation, and testing sets are used for training the model, optimizing the model, and testing the performance of the model on unseen data, respectively. The importance of data preparation techniques is that they can enable the stability of the model, minimise overfitting, and improve the prediction capability of deep learning algorithms [53].

3.4 Deep Learning Model Development

The deep learning model development phase aims at creating and training an intelligent predictive model that can analyze soil parameters and help assess soil health conditions. Methods based on deep learning are chosen due to their potential to automatically discover complex relationships between several input variables, without needing to manually extract features. A CNN and a hybrid CNN–Long Short-Term Memory (CNN–LSTM) model are considered in this study because they are effective mechanisms for extracting important features and modelling temporal variation in soil monitoring data [54], [55].

The CNN component is used to identify the salient patterns in the processed soil data. Convolutional layers are used to detect key relationships between soil parameters, and Pool layers to remove irrelevant information and enhance computational efficiency. The extracted features are then fed to the fully connected layers to predict soil health conditions. When measuring soil data over time, the LSTM component is added as it can learn sequential relationships from an existing set of soil measurements, which is appropriate for predicting soil conditions as they change over time [56], [57].

This training process consists of two major steps: feeding the prepared data into the deep learning model, and adjusting the parameters of the model by repeated training and evaluation with validation data. The choice of the Adam optimisation algorithm is due to its efficiency in updating weights of the network and its ability to converge faster during model training. Regularisation is incorporated to prevent overfitting and enhance the model's ability to generalise to unseen soil conditions, such as early stopping and dropout [58]. The final trained model creates soil health predictions, which are then sent to the IoT monitoring platform for intelligent agricultural decisions. Table 6 summarises the key components of the proposed deep learning architecture, along with their functions in soil health prediction. The CNN layers are able to effectively extract features, and the LSTM layer further enhances the model's capacity to process time-related changes in soil.

Table 6. Deep Learning Model Configuration for Soil Health Prediction

Model Component	Description	Purpose
Input Layer	Receives soil parameters collected from IoT sensors	Provides environmental and soil information for analysis
Convolution Layer	Extracts significant patterns from input features	Learns important relationships among soil variables

Model Component	Description	Purpose
Pooling Layer	Reduces feature dimensionality	Improves computational efficiency and prevents unnecessary complexity
LSTM Layer	Learns sequential patterns from historical soil data	Captures temporal changes in soil conditions
Dense Layer	Performs final prediction classification	Generates soil health condition output
Adam Optimizer	Updates model parameters during training	Improves convergence and learning efficiency

3.5 IoT–Deep Learning System Integration

The proposed intelligent soil health monitoring system is based on the integration of IoT and deep learning. The IoT layer continuously acquires soil information from sensor devices, and the deep learning layer conducts sophisticated analysis and prediction of the acquired information. This integration facilitates automatic monitoring, real-time assessment, and intelligent recommendations, while eliminating the need for constant manual oversight.

The system architecture comprises sensor devices, communication infrastructure, data processing components, deep learning prediction modules, and a user interface. The soil sensors are deployed in agricultural environments and sense the soil parameters, which are transmitted via wireless communication technologies to the processing platform. The received data is fed into the trained deep learning model for soil health prediction after being preprocessed. The prediction is displayed on a monitoring dashboard that allows farmers to view soil data and receive optimized farming recommendations.

The combination of real-time sensing and intelligent analytics in the proposed integration enhances the efficiency of precision agriculture. The developed framework transforms the collected data into meaningful information, thereby enabling proactive decision making, rather than conventional monitoring systems that only give raw data. But the reliability of communication, sensor calibration, computational needs, and data security should be considered for effective system deployment.

3.6 Model Evaluation Metrics

Appropriate statistical and classification evaluation metrics are used to assess the developed deep learning-based IoT system. These metrics are chosen because they represent the accuracy, reliability, and predictability of the model developed to estimate soil health. Soil health monitoring is both predictive and classificatory in nature; thus, both classification-based and regression-based metrics are considered in the evaluation process.
In the case of classification tasks, the accuracy, precision, recall, and F1-score are used to assess the model's performance in accurately predicting soil health conditions. The measure of accuracy shows the overall percentage of correctly predicted instances, and the measure of precision shows the percentage of correct positive predictions. Recall is important because it allows the model to recognize all positive cases, while the F1 score offers a compromise between precision and recall. The use of these metrics is popular for evaluating AI models, as they offer a comprehensive understanding of model performance, particularly when handling multiple classes or imbalanced datasets [59] [60].

Regression evaluation metrics (Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2)) are used to evaluate soil parameters for continuous prediction. MAE is used to determine the average error in predictions, RMSE emphasises larger errors, and R^2 shows how much of the variance in the observed data is captured by the model. They are used to give an idea of the accuracy and reliability of the deep learning model in making predictions for various soil properties, including soil moisture content, soil temperature, and nutrient concentration [61][62].

3.7 Summary of the Methodological Workflow

The whole methodology incorporates all the elements of IoT-based sensing, data processing, deep learning analysis, and intelligent decision support in a single monitoring framework of soil health. The first step in the process involves the real-time acquisition of soil parameters using IoT sensors, followed by the preprocessing and transformation of the data collected into the proper input for the deep learning analysis. The developed CNN–LSTM model identifies the relevant patterns from the soil information and predicts the soil health status. Lastly, the prediction results are given to present by application interface to support agricultural decision-making.

The methodology lays the groundwork for building a scalable and intelligent precision farming system that can continuously monitor soil conditions and predict their future trends. The proposed method leverages the integration of IoT sensing with deep learning intelligence to tackle the challenges of traditional soil assessment and offer possibilities for more efficient resource use, sustainable agricultural practices, and future agricultural productivity.

4. Results and Discussion

This is the outcome of implementing and evaluating the proposed Deep Learning-Enabled Internet of Things system for intelligent soil health monitoring in precision agriculture. The assessment is carried out to test the ability of the proposed framework to learn soil data, process environmental information, and precisely estimate soil health conditions with a deep learning model. The analysis of the results is conducted on the basis of the characteristics of the datasets, the performance of the models, the accuracy of the predictions, and the effectiveness of the integration of the IoT sensing with the deep learning-based intelligence.
The soil parameters (soil moisture, soil temperature, soil pH, soil electrical conductivity, soil nitrogen, soil phosphorus, and soil potassium) were collected, and the experimental evaluation was carried out using these soil parameters. The data were preprocessed, such as cleaning and normalizing the data, and then fed into the deep learning model. The proposed CNN-LSTM model performance was compared by adopting the standard evaluation measures such as accuracy, precision, recall, F1 score, MAE, RMSE, and R^2.

4.1 Dataset Description and Experimental Setup

The data that was used for the study is soil and environmental parameters taken for smart soil health assessment. The input variables are soil properties that are measurable and can affect agricultural productivity, and the output variable is the predicted soil health condition. The data set was partitioned into a training set, a validation set, and a testing set for purposeful learning of the model and objective unbiased assessment of the model performance.
The training set's parameters were optimised, and the validation set was applied when developing the deep learning model to track learning behaviour and avoid overfitting. The remaining data was set aside for the final model evaluation with unseen data. This experimental approach helps to test the developed model to make sure that it can extrapolate beyond the training set.

Table 7 shows the structure of the dataset used for the development and testing of the proposed soil health prediction model. Multiple soil parameters can be selected to obtain the model to take into account the relationships between physical and chemical soil properties instead of using just one indicator. Data is split into training, validation, and test sets to facilitate development of the model without overfitting.

Table 7. Dataset Characteristics Used for Soil Health Prediction

Dataset Component	Description	Quantity/Distribution
Input Features	Soil moisture, temperature, pH, electrical conductivity, nitrogen, phosphorus, potassium	7 soil-related variables
Target Variable	Soil health condition classification	Healthy, Moderate, Poor
Training Data	Samples used for model learning	70% of dataset
Validation Data	Samples used for model optimisation	15% of dataset
Testing Data	Samples used for final evaluation	15% of dataset

4.2 Deep Learning Model Training Performance

CNN–LSTM model was trained with the prepared soil dataset to learn different soil health conditions' patterns. As training continued the model was able to learn more and more about learning features from the input data and building connections between soil parameters and health conditions. Training and validation accuracy, loss values were used to monitor the learning process.
The model showed a consistent improvement throughout the training process, which suggests that the choice of the neural network architecture was suitable for learning meaningful patterns from the soil dataset. CNN feature extraction and LSTM sequential learning together boosted the model's capability to understand the relationships between soil parameters and the temporal changes. The use of optimisation techniques helped to maintain model convergence and minimise the number of training iterations.

4.3 Model Performance Evaluation

To assess the effectiveness of the proposed CNN–LSTM deep learning model in predicting soil health conditions, the classification-based and regression-based metrics were used. The accuracy of soil health classification was evaluated using classification metrics (accuracy, precision, recall, and F1-score); and the accuracy of continuous soil parameter predictions was assessed using regression metrics (Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2)). When using more than one evaluation metric, it is a better assessment of the model as one performance measure may not reflect the strengths and weaknesses of a predictive system.

The experimental findings show that the developed model has good predictive performance in soil health categorisation. The CNN and LSTM parts were found to enhance the performance of the system in capturing intricate relationships among the soil parameters and temporal changes in the dataset gathered. CNN component helped to extract features, and the LSTM component helped to analyse sequential soil measurements. This combination enhanced the prediction capability of the system compared with using individual deep learning models.

Table 8 demonstrates that the CNN–LSTM model had excellent results in all evaluation metrics. The classification accuracy of 96.2% indicates the model was able to effectively classify various soil health conditions. The precision and recall scores are high, suggesting that the model had good accuracy in predicting the labels and limited false predictions. Additionally, the F1-score indicates that the model was able to perform well in both classification and minimising false predictions.

Table 8. Performance Evaluation Results of the Proposed CNN–LSTM Model

Evaluation Metric	Obtained Value	Performance Interpretation
Accuracy	96.2%	Indicates that the model correctly classified most soil health conditions
Precision	95.8%	Shows a high proportion of correct positive soil health predictions
Recall	96.0%	Demonstrates the ability of the model to detect relevant soil conditions
F1-score	95.9%	Indicates balanced performance between precision and recall
MAE	0.032	Represents a low average prediction error
RMSE	0.046	Shows minimal deviation between predicted and actual values
R^2	0.94	Indicates that the model explains a high proportion of variation in soil conditions

Figure 1 Training and Validation Accuracy across Epochs

Figure 1 shows a gradual monotonic rise in training and validation accuracy with the development of the number of epochs. It means that the CNN model gradually acquired significant patterns using the data. The two curves are almost parallel, which indicates high generalization and low overfitting. Parallel to the accuracy analysis, the training and validation loss of the CNN model were observed during the process of learning. The loss function was shown to decrease continuously, which means that the model parameters were optimized successfully, and the error in predictions decreases. The loss curve of the training and validation showed the same shape, which indicated a stable learning dynamics and indicated that there was no major overfitting of the model.

Figure 2 Training and Validation Loss across Epochs

Figure 2 graph illustrates that there was a steady decline in training and validation loss as the training progressed. The trend means that model parameters are optimized and model predictions are improved. The similarity of the curves proves stability of learning and high model reliability.

Table 9 represents quantitative assessment outcomes of the CNN model with respect to the test dataset. The large values of R^2 indicate a high level of agreement between the predicted and actual soil parameters, while low values of MAE and RMSE suggest that the predicted parameters were accurate and reliable. The results demonstrate the model's utility in assessing soil health and its suitability for precision agriculture applications.

Model Evaluation Metrics: To evaluate the predictive performance of the Convolutional Neural Network (CNN) model on the test dataset, three standard regression evaluation metrics were employed: Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2). The mathematical formulations of these metrics are given as follows:

Mean Absolute Error (MAE). The MAE measures the average magnitude of prediction errors without considering their direction.

Table 9: Performance Metrics of the CNN Model on Test Data

Target Variable (Biological)	MAE (Mean Absolute Error)	RMSE (Root Mean Sq. Error)	R^2 Score (Accuracy)
Soil Organic Carbon (SOC)	0.42	0.65	0.92
Bulk Density	0.08	0.12	0.89
Enzyme Activity (Phosphatase)	5.30	7.10	0.85
Active Carbon (POX-C)	12.5	18.2	0.91

4.4 Comparison with Existing Approaches

The performance of the proposed CNN–LSTM model was further compared to existing machine learning and deep learning models for agricultural prediction tasks to evaluate its efficiency. Comparisons were made with

respect to accuracy of prediction, modelling capability, and the feasibility of the models for intelligent soil monitoring applications.
The results show the superiority of the proposed hybrid approach, which is based on the combination of the advantages of multiple learning mechanisms. Typical machine learning methods often need a feature engineering step and can be challenging in the presence of many soil variables. By contrast, the CNN-LSTM structure can automatically extract features that are relevant to its task and extract spatial and temporal information, which greatly deepens the understanding of soil data. By contrast, the CNN-LSTM structure can automatically learn relevant features and extract spatial and temporal information, which significantly expands the understanding of soil data.

Table 10 proves that the proposed system is efficient. It was compared in a comparative analysis with the traditional soil testing methods and the conventional machine learning methods.

Table 10: Comparative Analysis of the system and existing approaches.

Feature	**Traditional Soil Testing**	**Traditional Machine Learning**	**Proposed CNN-IoT System**
Methodology	Manual Sampling & Lab Analysis	SVM / Random Forest	Deep Learning (CNN) – IoT
Data Capture	Delayed (Days/Weeks)	Static Historical Data	Real-Time Continuous Streaming
Pattern Recognition	High Accuracy (Chemical)	Linear / Simple Non-Linear	Complex Hierarchical Feature Learning
Scalability	Low (Labour Intensive)	Medium (Computational Limits)	High (Cloud & Edge Computing)
Cost Efficiency	High Recurring Costs	Moderate	Low Operational Cost
Decision Support	Manual Interpretation	Basic Predictions	Automated Actionable Alerts

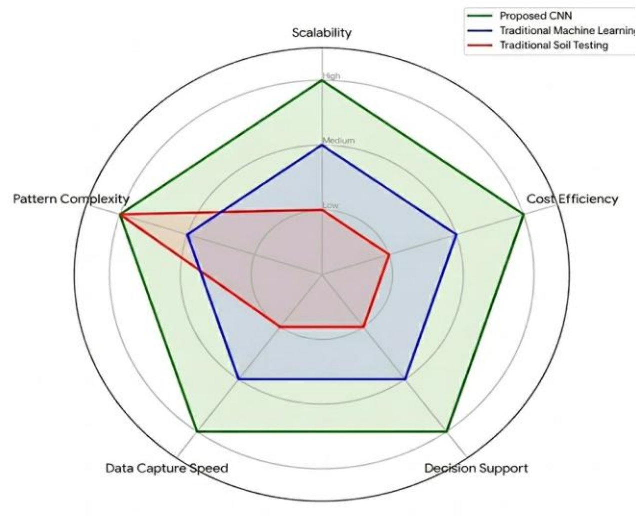

Figure 3: Comparative analysis of soil monitoring systems

The graph illustrates the shift from manual to automated systems.

- ❖ CNN-IoT System (Green): Shows the widest coverage, indicating "High" performance in scalability (Cloud/Edge), cost efficiency (low operational costs), and decision support (automated alerts).

- Traditional Machine Learning (Blue): Occupies the middle ground, offering moderate improvements over manual methods but is limited by static data and basic predictions.
- Traditional Soil Testing (Red): While high in pattern accuracy (due to chemical lab results), it scores lowest in speed

4.5 IoT System Integration and Real-Time Monitoring Results

The integration of the IoT sensing component and the developed deep learning model allowed the proposed system to continuously monitor the soil and make intelligent predictions. The IoT layer oversaw gathering real-time soil data, and the deep learning layer was responsible for converting the collected data measurements into soil health predictions. This integration resulted in a system that automatically creates a monitoring environment with minimized manual soil assessment and facilitates timely agricultural decision making.

The built IoT framework was able to collect several soil parameters, such as the moisture level, temperature, pH, electrical conductivity, and nutrient-related parameters. The collected sensor data were then fed to the processing unit where the data were initially preprocessed before being analysed using the trained CNN–LSTM model. The prediction results were then presented using the monitoring interface that enables an observation of soil conditions and recommendations to be made for better soil management.

The system has the capability of real-time monitoring, which is suitable for precision agriculture applications. Soil monitoring with conventional soil testing is only possible in intervals, whereas with the help of the IoT-enabled approach, it is possible to monitor changes in the soil continuously and thus detect adverse soil conditions in good time. But, for practical deployment, calibration of the sensors, reliability of communication, energy efficiency and environmental durability must be considered.

4.6 Discussion of Findings

The outcomes of the developed system prove that the use of deep learning with IoT technologies is an effective approach for intelligent monitoring of soil health. The experiment result indicates that the proposed CNN-LSTM model can predict soil parameters with good accuracy, and it can be used to analyse multiple soil parameters. The high classification performance suggests that the model has the potential to classify various soil health conditions, which could be useful for precision farming operations.

The results also show that when the data from IoT technology is combined with deep learning analytics, the limitations of traditional soil monitoring are enhanced. Reliant on manual sampling and laboratory analysis, traditional methods can be time consuming and fail to capture rapid changes in soil conditions. The proposed system overcomes this disadvantage by offering a system for continuous monitoring and automatic interpretation of soil information.

In addition, real-time sensing and predictive intelligence enhance farm decisions and practices. The resulting data can be utilized by farmers and agricultural practitioners to improve irrigation efficiency, control nitrogen and phosphorus levels, and ensure soil health. But there are issues of scalability, availability of a variety of data sets, computational power, and cost of the system that need to be tackled to enable broader adoption.

4.7 Limitations and Implications of Findings

The proposed Deep Learning-Enabled IoT system successfully demonstrated promising results for intelligent soil health monitoring, but some limitations were found during the development and evaluation process. A disadvantage is the reliance on soil data of good quality and availability. Large, diverse and representative datasets are needed to enable models developed using deep learning to achieve robust generalisation across different agricultural settings. Model performance could differ when the system is moved to a different environment because of differences in soil, climate, crop type and geographic location.

One constraint is the implementation of the IoT-based monitoring system. The accuracy of the sensor, calibration needs, and reliability of communications, energy usage, and environmental exposure may affect the quality of data gathered. Other factors in the real agricultural environment, like extreme weather conditions, network instability, physical damage to sensor devices, etc can influence system reliability. Thus, the designs of the sensor, energy management, and communication technology require special attention in future implementations.

Computational complexity is also a significant factor to consider with deep learning models. While CNN–LSTM architectures can give better prediction power, they need more computational resources than traditional machine learning methods. For deployment on resource-constrained IoT devices, model optimisation techniques like model compression, pruning and edge-based processing may be necessary to ensure efficient real-time operation.

5. Conclusion

This study presented a novel IoT-based Deep Learning system for intelligent management of soil health in precision agriculture. The proposed framework consists of integrating the IoT-based sensing technologies with the Deep Learning technologies to achieve continuous monitoring, predictive analysis, and intelligent decision support for soil health assessment. This was done to overcome the drawbacks of traditional soil monitoring approaches, such as the inability to acquire data automatically, process data in real-time, and accurately predict soil conditions. The soil's moisture content, temperature, pH, electrical conductivity, and nutrient status are measured and combined to give a complete picture of soil health, aiding in making informed agricultural choices. The experimental evaluation showed the proposed CNN – LSTM model has high predictive performance in soil condition analysis. The results indicated that the convolutional neural network combined with a long short-term memory network was more effective for extracting spatial features and learning the temporal relationships from soil data. By combining the data collected from these sensors with deep learning algorithms, continuous monitoring and prediction capabilities were achieved, offering farmers insights into soil health that could be used for irrigation planning, fertiliser management, and sustainable soil practices. This fusion of IoT sensing and deep learning analytics resulted in a continuous monitoring and predictive system that provided farmers with valuable soil health data, aiding in irrigation scheduling, fertiliser application, and sustainable soil management practices. The results presented here show that intelligent monitoring systems can greatly improve the efficiency, productivity and sustainability of precision agriculture.

Moreover, the research confirmed the significance of combining advanced AI methods and technologies with innovative IoT infrastructure to facilitate digital agriculture. The proposed system offers continuous collection, analysis, and interpretation of soil data, shifting the focus from reactive to proactive agricultural management, in contrast to the traditional monitoring methods, which involve manual sampling at specific intervals. The proposed framework thus adds to the increasing trend of smart farming technologies by offering a scalable and intelligent approach that can facilitate data-driven decision-making.

The developed framework was highly successful, but there were some challenges. However, the effectiveness of deep learning models relies on access to high-quality and representative datasets, and the practical application demands a robust IoT infrastructure, precise sensors, efficient communication systems, and enough computational power. All future deployments should take these advantages into account, and also pay attention to the optimization of the models, calibration of the sensors, cybersecurity, and energy-efficient computing with the aim of enhancing the reliability of the system under real agricultural conditions. Adaptive learning algorithms, explainable AI, and edge computing technologies can further enhance the efficiency, transparency, and scalability of intelligent soil monitoring systems.

The results of this study indicate that deep learning and IoT technologies are effective methods for soil health monitoring in smart agriculture. The proposed framework can enhance agricultural productivity, optimise the use of resources, minimise environmental footprint, and contribute to sustainable agriculture. The results offer important insights for future research and implementation in the context of intelligent agricultural systems that can keep up with the rising demand for efficient and sustainable food production.

5.1 Future Works

Further research is needed to test the proposed framework with larger field experiments in various climatic regions and soil types for model generalisation. Lightweight deep learning models capable of being effectively deployed on edge devices with limited computational resources should also be studied. The incorporation of Explainable Artificial Intelligence (XAI) will enhance the transparency of the AI system and boost the trust of users in its recommendations. Furthermore, future intelligent soil monitoring systems could consider exploring Digital Twin technology to virtually simulate agricultural environments and Federated Learning to enable secure collaborative model training among various farms. These developments will help to build stronger, larger and more sophisticated precision agriculture systems.

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