SOIL NUTRIENT PREDICTION AND CROP PREDICTION RECOMMENDATION SYSTEMS USING IOT AND AI TECHNIQUES: CURRENT TRENDS AND CHALLENGES

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Uwadia O. A., Dahunsi F. M. (2026): Soil Nutrient Prediction and Crop Recommendation Systems using IoT and AI Techniques: Current Trends and Challenges. FUTA Journal of Engineering and Engineering Technology 20(special), 35-43

Received Date: 15.01.2026 **Accepted Date: 10.02.2026**

Abstract
The emergence of the Internet of Things (IoT) and Artificial Intelligence (AI) technologies has transformed the agricultural industry by offering promising solutions to issues relating to crop recommendation and soil nutrient prediction systems. Due to the urgent need for sustainable agricultural practices, IoT and AI-based soil nutrient prediction and crop recommendation systems have drawn significant attention recently. Recent advancements have introduced innovative models capable of monitoring soil health, predicting nutrient deficiencies, and recommending suitable crop varieties tailored to a specific environment with varying climatic conditions. This paper presents recent developments in IoT and AI-driven technologies that improve smart farming by providing data-driven support and real-time monitoring of soil health. AI models are capable of analysing data from sensors, satellite imagery, and past history to accurately predict soil nutrients and recommend crops, ensuring efficient and sustainable agricultural practices. Despite the advancement in technology, data quality, model interpretability, cost, and accessibility pose challenges that hinder the widespread adoption, particularly among smallholder farmers. The future of smart farming systems lies in overcoming existing barriers and advancing technology to offer scalable, affordable, and user-friendly solutions. Various methodologies and approaches, such as hybrid and ensemble models that combine data-driven AI methods with domain-specific agronomic knowledge, have demonstrated improved reliability and accuracy. With emphasis on some of the important soil parameters such as nutrients, moisture, power of Hydrogen, temperature, relative humidity, and electrical conductivity, this paper discusses the roles of IoT and AI in enhancing the efficiency and precision of Smart Farming. Furthermore, this paper provides insight into current trends and techniques in Smart Farming by synthesising findings from a range of studies on advanced technologies.

Keywords: *Precision Agriculture, Soil Nutrient Prediction, Crop Recommendation, Internet of Things, Artificial Intelligence, Soil Sensor, Machine Learning, Deep Learning, Smart farming, Sustainability.*

Introduction

In Nigeria today, many small-scale farmers rely solely on agriculture as their major source of livelihood. However, because of the country's varied climate, different soil types, and a lack of knowledge about crops, farmers find it difficult to make important decisions about which crops to grow and the yields they anticipate. Losses occur when crops do not produce the anticipated amount of harvest. Many farmers still use traditional methods to prepare their soils, but they often overlook the impact of dynamic changes in soil nutrient content on crop yield variability over time. Meanwhile, smallholder farmers increase pesticide and fertiliser applications in an attempt to boost yields, inadvertently reducing soil fertility through increased toxicity and diminished water-holding capacity (Saha *et al.,* 2020). On the other hand, farmers find conventional soil testing techniques, such as Laboratory-based Soil Testing (LST) or Soil Test Kits (STK), unfriendly due to unfamiliarity with these technologies and find it challenging to interpret the results. Despite their accuracy, they are time-consuming and labour-intensive. Smart

Farming Management System integrates AI and IoT technologies to provide data-driven support in real-time for farmers to predict soil nutrient levels and recommend crops or fertilizer regimes, enabling them to make well-informed decisions that will boost agricultural productivity while minimising environmental impact (Zhang *et al.,* 2021). This system is driven by global challenges such as soil degradation and the growing need for sustainable food production (Mishra *et al.,* 2021).

Table 1 presents an overview of various types of soil sensors indicating the measured parameters, highlighting their advantages and limitations.

Soil Nutrient Prediction and Crop Recommendation Systems are two key areas among several applications of IoT and AI in agriculture.

Table 1: Overview of Soil Sensor Types and Sensing Technologies: Advantages and Limitations

Type of Sensors	**Parameters Measured**	**Advantages**	**Drawbacks**
Moisture Sensors	Soil moisture	Over-irrigation can be avoided; Improved water management; Improved crop yield	High-precision soil sensors can be expensive; Sensitive to different soil types and textures
pH Sensors	Soil pH	Determines nutrient availability; Enhanced crop productivity; Optimised Fertiliser application	Requires frequent calibration; expensive high-precision sensors
Nutrient Sensors	Macronutrients and micronutrients	Provides real-time nutrient level; Optimised application of fertiliser; Enhanced crop productivity	Sophisticated Nitrogen sensors are expensive; achieve low accuracy for micronutrients; large-scale implementation can be expensive.
Temperature Sensors	Soil Temperature	Predict the planting and germination period; influences crop growth and microbial activity; pest and disease control	Not applicable to deep-rooted crops; affected by the time of day and weather conditions
Electrical Conductivity Sensor	Soil nutrient content and salinity	Real-time indicator of soil health status; early detection of salinity issues; estimates nutrient level based on electrical conductivity	Frequent maintenance and calibration; susceptible to interference from soil texture and mineral composition; high salinity limits the sensor capabilities

Table 2: Communication Protocols used in transmitting soil data and their characteristics

Communication Protocol	**Characteristics**
Bluetooth	Low-power consumption; short-range; low data transfer requirements; useful in small-scale IoT setups; suitable for local networks; not suitable for large farmland.
Zigbee	Low-power; low data rate; widely used for Wireless Sensor Network; offers long range and reliable for large farmland when compared to Bluetooth.
LoRaWAN	Low-power; visible over long range up to 10km; highly energy efficient; suitable for large agricultural fields
NB-IoT	Low-power WAN; supports long-distance transmission of data; suitable for agricultural IoT systems in remote areas with limited connectivity.

Table 2 lists a few communication protocols that are used to send data to a centralised system, emphasising their key features in terms of transfer rate, range and power consumption

This paper highlights the key roles of IoT and AI in sustainable farming and addresses the challenges associated with implementing an integrated IoT- and AI-based system. This review also discusses IoT-based soil sensing technologies, current trends, and future directions for sustainable, technology-driven smart farming systems.

IoT-based Soil Sensing for Soil Nutrient Prediction

Farm Management System that utilises an IoT-based soil sensing technique provides a well-structured framework for gathering soil data from sensors and sending it to a centralised system, such as a cloud platform or local databases, for analysis. In some IoT-based systems, data collected is processed and analysed locally at the sensor level using edge computing before it is transmitted. Cloud platforms like Google Cloud are used by the IoT-based Soil Nutrient Prediction System for data aggregation, storage, and analysis, making it accessible for cloud computing services, AI algorithms analysis, and accessing soil data from anywhere.

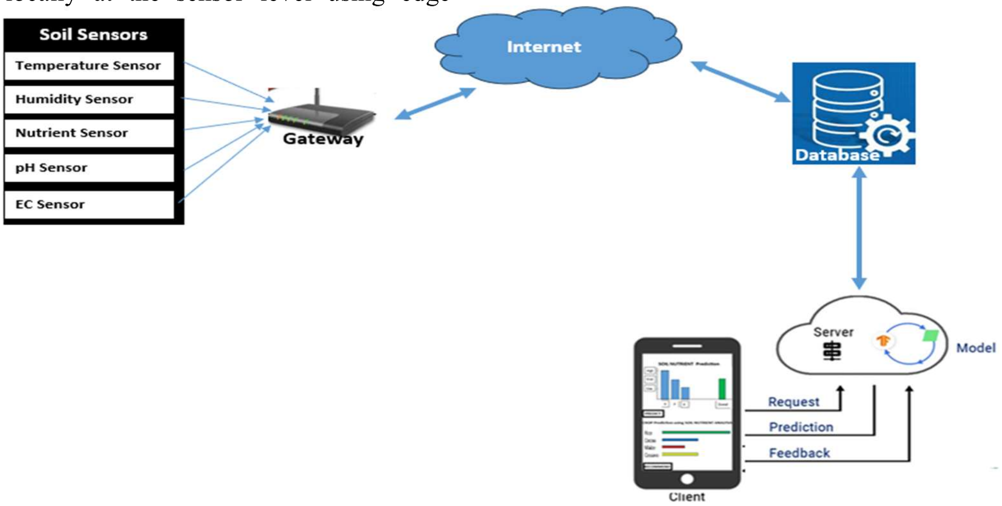

Figure 1: Real-time Monitoring and Management of an Integrated IoT-enabled and AI Smart Farming System

AI-based Soil Nutrient Prediction Systems

Soil health is a critical factor in determining agricultural productivity. Accurate prediction of soil nutrient levels is essential for optimising fertiliser application and improving crop yields. In addition to being expensive and time-consuming, conventional soil testing methods necessitate specialized knowledge to interpret the results; in order to overcome these obstacles, AI-based soil nutrient prediction models analyse enormous datasets of soil data gathered from IoT sensors and produce precise forecasts of soil nutrient levels and soil health.

The integration of diverse data sources using AI frameworks showcases a significant breakthrough in the application of AI in soil nutrient level prediction systems. These multimodal systems enhance the spatial and temporal accuracy of nutrient predictions by integrating satellite imagery, IoT soil sensor data, and climatic variables. Furthermore, AI models are capable of forecasting the optimal nutrient requirements for a particular soil type by utilizing historical data on crop yields and weather patterns. This will guide farmers in the use of fertiliser and avoid over-application, which could harm the environment (Zhang *et al.,* 2020b).

Deep Neural Network, Support Vector Machine, and Random Forest are among the various AI models that have been modelled to estimate Soil Nutrient Levels (Sinha *et al.,* 2019; Zhang *et al.,* 2020b). These models are good at managing high-dimensional and non-linear relationships between nutrient availability and soil characteristics (Zhang *et al.,* 2019), which conventional methods cannot achieve.

In 2018, Chou *et al.,* modelled soil nitrogen content using linear regression, considering environmental factors such as temperature and precipitation.

Studies have utilised Support Vector Machines (SVMs) for classification tasks to identify soil nutrients and types (Lui *et al.,* 2019; Gao *et al.,* 2020b). Their capacity to manage high-dimensional data spaces makes them particularly well-suited for analysing sensor-derived inputs.

In a more recent study, Zhao *et al.,* (2021) investigated Long Short-Term Memory and Recurrent Neural Networks to capture the dynamics of variation in nutrients, particularly in relation to seasonal changes and fertilisation regimes.

Artificial Neural Networks (ANNs), including advanced Deep Learning architectures, have been increasingly utilised for predicting nutrients. These models have demonstrated excellent predictive accuracy for a number of soil characteristics, including macronutrients, and can identify complex patterns in large datasets (Kumar *et al.,* 2020; Zhao *et al.,* 2021; Jain & Sharma, 2023). Notwithstanding their potential, the computational complexity and challenge of acquiring a sizeable labelled dataset

prevent this application from being widely adopted (Gao *et al.,* 2020a).
Table 3 provides a summary of existing studies on Soil Nutrient Prediction and Crop Recommendation Systems, highlighting the approaches, methods and identified constraints.

Table 3: Literature Review on Soil Nutrient Prediction and Crop Recommendation Systems – Authors, Approaches, Methods, and Limitations

Author & Year	**Approach**	**Methods**	**Limitations/Drawbacks**
Ersin *et al.,* 2023	Based on soil and climatic conditions. (Crop Recommendation)	Hoeffding Tree, Bayes Net, and Naïve Bayes Classifier.	Large data sets for model training can be computationally demanding.
Garg & Alam, 2023	Based on Soil and Environmental conditions. (Crop Recommendation)	Wrapper-PART-Grid	Requires hyperparameter optimisation
Iniyan *et al.,* 2023	Based on soil and environmental conditions. (Crop Recommendation)	Decision Trees, LSTM, Gradient Boost Regression, Linear Regression, Lasso Regression, PLS Regression, Elastic Net and Ridge Regression	No discussion on the Models' interpretability
Kanaga Suba Raja *et al.,* 2023	Based on soil pH and nutrient levels. (Crop yield Prediction)	CNN, RNN, HNN	Requires large computational resources for model training
Escorcia-Gutierrez *et al.,* 2022	Based on Soil fertility level and crop needs. (Soil Nutrient and pH classification)	DL, GRU, DBN, Bi-LSTM	Achieved low accuracy compared to other techniques
Nguyen *et al.,* 2022	Based on Digital Elevation Model derivatives, Sentinel-1 and Sentinel-2 data. (Soil Moisture Prediction)	For feature selection, RFR, XGBoost, SVM CBR and GA were used.	There is need to evaluate the framework across a large-scale region with diverse land-use characteristics.
Ou *et al.,* 2021	Based on Hyperspectral remote sensing image data. (Soil Properties Prediction)	DNN, GA, SVR and regression methods were used.	The model was sensitive to the training dataset and was never tested on a substantial amount of data.
Dharumarajan *et al.,* 2020	Based on Covariates datasets. (Nutrient Prediction)	QRF and RK	Achieved low accuracy due to errors in locating old coordinates.
Mosavi *et al.,* 2020	Based on the land, soil properties and climatic conditions. (Soil Nutrient Content Prediction)	Weighted subspace random forest, Gaussian process, and Naive Bayes	Data collection and sampling are not the same; RMSE, R^2 and MAE factors are not considered in the performance evaluation.
Bondre & Mahagaonkar, 2019	Depends on soil location information, historic data and soil nutrients. (Soil classification, crop yield and fertiliser Prediction)	Random Forest and SVM	Achieved low accuracy for soil classification
Riese *et al.,* 2019	Based on soil moisture and land cover. (Soil moisture Prediction)	Unsupervised SOM, Supervised SOM, semi-	MAE and RMSE factors were not taken into consideration.

		Supervised SOM and RF	

Table 4: Summary of Several approaches, Limitations and Future research directions for advanced sensing Technologies

Aspect	Approaches	Limitations	Future Directions
1. Soil sensing in an Open field	▪ Adoption of Hybrid Sensor ▪ Fusion of multiple sensor data	○ Lacks the ability to capture spatial variability at a wide field. ○ Dependence on point-based data. ○ Poor resolution of conventional sensors.	• Design and development of self-calibrating, miniature sensors. • Integration of machine learning approaches for site-specific nutrient management.
2. Hydroponic systems	▪ Ion-specific monitoring sensors in real-time ▪ Durable and reliable sensor materials	○ Measures only Electrical Conductivity and pH ○ Lacks the ability to detect specific ions ○ Sensitivity to variation in temperature	• Self-adjustable automated system based on dynamic threshold values. • High Temporal frequency sensing technologies.
3. Integration and analysis of data	▪ ML-based model for prediction of soil nutrients ▪ IoT- enabled systems for the collection of data in real-time	○ Limited amount of sizeable data for timely intervention ○ Averaged Dataset	• Optimised Machine Learning based algorithm for predictive analysis. • User-friendly decision-support platforms
4. Variable Environmental Conditions	▪ Robust sensors with environmental resilience ▪ Integrated multi-modal sensing systems.	○ Environmental impact of temperature, humidity, and pollutants on sensor functionality and stability	• Development of adaptive sensors for varying environmental conditions. • Integrating environmental data into soil nutrient management systems.
5. Intelligent agricultural systems	▪ Algorithms that can adapt to real-time changes ▪ Smart sensor-based systems for remote monitoring	○ Pre-set thresholds that are not sensitive to dynamic changes ○ Existing systems lack flexibility	• Real time feedback for system correction. • Scalable automated Infrastructure for small- and large-scale farms

IoT and AI integration for Sustainable Smart Farming

The integration of IoT and AI in sustainable smart farming enables field monitoring and management effectively. In Soil Nutrient Prediction and Crop Recommendation Systems, IoT sensors collect real-time soil data (temperature, pH, moisture, electrical conductivity, relative humidity and nutrient content level) that are necessary to monitor soil health and environmental conditions (Rainfall, wind speed, other local climate data) which are vital for planning crop planting schedules, forecasting weather patterns, making informed decisions on irrigation, pesticide use and harvesting (Prasad *et al.,* 2020; Jejurkar *et al.,* 2021).

AI technology is essential for processing and analysing data from a variety of sources, such as soil sensors, weather stations, and past crop performance records. These models can forecast soil nutrient levels by finding patterns in the data, which enables farmers to maximise fertiliser application, reduce runoff, boost crop yields, and support environmental sustainability (Zhang *et al.,* 2020a), while the IoT provides real-time data collection, AI processes this data into actionable insights. IoT-AI based smart farming enables real-time monitoring and automated decision-making, thereby reducing the need of human intervention and increasing the productivity of farming operations (Khan *et al.,* 2020). In Figure 1, an integrated IoT-enabled and AI smart farming system is monitored and managed in real-time.

Real-time Monitoring: With this integration, farmers can continuously monitor soil health and environmental conditions, and as well turn on irrigation when needed by deploying a network of IoT sensors throughout a designated area to respond proactively to changing environmental conditions and ensure crops receive the proper nutrients in specific areas with limited resources, which is crucial for sustainable farming (Jejurkar *et al.,* 2021). This integrated technology optimizes resource use, supports data-driven decision making, boosts agricultural productivity, and mitigates negative environmental effects.

Automated and Improved Decision-making Process: IoT-AI based Soil Nutrient Prediction and Crop Recommendation System has helped farmers improve their chances of selecting suitable crops, higher yields, and make long-term decisions about crop rotation by analysing soil health, weather patterns, past yields, and climate forecasts (Thorp *et al.,* 2018; Singha *et al.,* 2023). This integrated system can as well provide information on droughts, floods, and crop conditions, such as pest attacks or nutrient deficiencies, so that farmers can take proactive measures like modifying irrigation schedules, applying fertiliser, or controlling pests, which enhances the sustainability and efficiency of farming operations (Saha *et al.,* 2020; Roy & Mishra, 2023). IoT-AI-based technologies have enabled the automation of farming tasks, including autonomous tractors, drones for crop surveillance, and robotic harvesting systems. These automated systems boost productivity, reduce production cost and eliminate the need for manual labour. Furthermore, more sophisticated and complex farming machinery that will assist with routine tasks as well as work autonomously based on AI-driven recommendations is expected to emerge in the future (Gao *et al.,* 2020b).

Current Trends on the Application of IoT and AI in Soil Nutrient Prediction and Crop Recommendation Systems

Smart Farming Management platforms that integrate IoT and AI in Soil Nutrient Prediction and Crop Recommendation Systems utilizes cutting-edge technologies to provide end users with information on soil health in real time, weather patterns, crop conditions, and resource usage, empowering them to take proactive decisions. This platform integrates mobile applications, various data sources (including IoT soil sensor data, crop yield history, environmental conditions, and remote sensing satellite data), and AI. Modern IoT-AI-based systems with user-friendly interfaces can provide low-level literate farmers with real-time soil information, recommendations, and decision-support visualisation. In addition, the application of this system is expanding into robotic weeding, drone-assisted crop monitoring, and Variable Rate Technology for applying fertiliser and pesticides.

The current trends shows that Smart Farming Systems are evolving towards efficient, sustainable, and data-driven solutions that are tailored to meet local needs.

Challenges and shortcomings of the existing IoT-AI based Soil Nutrient Prediction and Crop Recommendation Systems

Despite advancements in IoT sensing Technologies and AI models, a few challenges still hinder the effective application of Soil Nutrient Prediction and Crop Recommendation Systems, as well as their widespread adoption. Some of these challenges are;

Data Quality and Availability: Developing accurate AI models requires extensive, high-quality soil data, which includes nutrient measurements, soil characteristics, and crop histories. Large-scale datasets are hard to get, even for soil, weather, and crop performance. Many regions lack current soil surveys because the traditional soil sampling method is labour-intensive (Zhang *et al.,* 2020a; Jain & Sharma, 2023). AI model Predictions become inaccurate due to datasets that are fragmented, noisy, and scarce (Mishra *et al.,* 2021). This problem is common in developing countries, where data on soil, weather, and crops are often scarce and difficult to get. AI models trained on sparse local data may become less robust and be unable to generalise across different regions and soil types (Liu *et al.,* 2019). A comprehensive initiative on data collection and deployment of a well-secured data sharing platform is necessary to get past this barrier, but such an idea is challenging.

Interpretability and Trust of AI-Driven Systems

Lack of transparency can reduce user trust and adoption, as farmers prefer clear, explainable recommendations. Explainable AI(XAI) techniques are gaining popularity due to their ability to give explanations for predictions, which are based on feature selection or rule-based justification (Singha *et al.,* 2023). Even though interpretable models may not be very accurate, they are at times preferred for their transparency. However, it remains difficult to strike a balance between interpretability and complexity. Users' comprehension and acceptance of crop recommendations can be improved by incorporating fuzzy logic and expert knowledge into AI systems. Furthermore, additional complications may arise due to sensor maintenance, hardware reliability, and stable internet connectivity when deployed in rural areas. Farmers who lack data science expertise, Data visualisation and a user-friendly interface will distil complex data into actionable insights.

Cost, Infrastructure, and Accessibility

Precision agriculture technologies depend heavily on reliable internet, electricity, and technical support, which are often lacking in rural communities. Infrastructure investments in sensors, data storage, and computational power are substantial. IoT sensor networks and mobile applications require continuous network access, reliable power sources, and specialised technical expertise for deployment and maintenance. Integration into cohesive solutions becomes more difficult due to a lack of standardization and interoperability across different systems and data formats (Zhang *et al.,* 2021). This technical difficulty of integrating climate sensor and remote sensing data calls for advanced data integration techniques

Wide-Spread Adoption and Socio-economic Challenges

Farmers may be reluctant to trust AI over traditional methods, especially if the suggestions do not match their own experiences. Widespread adoption may also be hampered by worries about data privacy and technological dependence. Farmers are more likely to accept workable solutions when they are included in the system design process. However, without government support or subsidies, smallholder farmers lack the funds to buy sensors, drones, or integrated IoT-AI setups. Furthermore, the inability to adapt to change and lack of digital literacy hinder adoption. Data privacy and ownership concerns arise when sharing farm information on cloud platforms.

User-centric design that provides voice assistance, explainable AI recommendations, and support for local languages can increase accessibility of this technology.

Despite proven technical feasibility, real-world implementation of these technologies faces critical barriers related to data limitations, model interpretability, cost, user acceptance, and Infrastructure. Resolving these issues is critical to transforming Crop Recommendation and Soil Nutrient Prediction Systems from research prototypes to useful tools for farmers to enhance crop productivity (Singha *et al.,* 2023).

Future Research Direction

Despite the potential of AI and IoT technologies in smart farming, challenges still exist in Soil Nutrient Prediction and Crop Recommendation Systems based on diverse soil data. The future of this system lies in advancing soil nutrient sensing technologies to improve scalability, affordability, and user-friendliness. An overview of existing sensing technology approaches, their limitations, and their prospective future directions for advancement is presented in Table 4.

Conclusion

IoT and AI-based systems for Crop Recommendation and Soil Nutrient Prediction have a significant impact on the agricultural industry. These systems have the potential to become indispensable components of modern farming practices, with sustained innovation and collaboration from stakeholders, as farmers are empowered to make data-driven decisions, they can boost output and advance global sustainability objectives. With advancements in machine learning, remote sensing, and cloud computing, the future of precision agriculture is promising, with the potential to improve yield, utilise resources more efficiently, and achieve greater sustainability. Apart from detecting nutrient deficiencies and offering customized suggestions for crop choice and nutrient management, IoT and AI-based integrated systems have proven to be capable of analying complex soil data. These systems' accuracy, accessibility, and scalability are being improved through advanced development in AI and IoT. However, it becomes imperative to tackle issues such as data quality, model transparency, infrastructure limitations, user engagement, financial constraints, and scalability in order to guarantee widespread adoption and long-lasting impact. Collaboration among agronomists, computer engineers, researchers, legislators and farming communities are essential for the successful adoption of these technologies. Such teamwork is essential to changing the agricultural industry. By providing farmers with the right resources, these systems can enhance crop quality and yields, which is crucial in addressing today's sustainability and food security challenges.

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