Smart Agriculture Using Artificial Intelligence and IoT: An Intelligent Decision Support System for Soil Analysis, Crop Recommendation, Fertilizer Management, and Multi-Cultivation

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Abstract: The convergence of AI and the IoT is revolutionizing agriculture by facilitating data-driven farming practices, boosting productivity, and driving sustainability. This research introduces an integrated, smart decision support system combining real-time data from the IoT with powerful AI models for optimizing fertilizer use, recommending appropriate crops, and creating effective multi-crop strategies. The suggested scheme gathers soil and environmental properties including moisture, temperature, nutrients and climatic parameters with the help of IoT sensors. The DL model module used includes Custom CNN, ResNet18, and Vision Transformer (ViT) models to make accurate soil category identification. The classified soil data along with the soil nutrients, especially NPK values, rainfall, temperature and historical agricultural information is used for crop recommendation and optimisation of fertilizers. ML algorithms such as LightGBM, CatBoost, XGBoost, and Extra Trees are tested for fertilizer recommendation with LightGBM getting the maximum classification acurity of 85.42%. The system also suggests suitable intercropping pairings based on the crop traits, nutrient uptake and utilization, environmental suitability and land productivity optimization, to ensure better soil health and productivity. Models are reliable and generalizable through hyperparameter tuning and cross validation. The entire model is embedded within a web/mobile decision support tool that can deliver real-time recommendations to farmers. The proposed solution results in reduced surpluses of fertiliser use, in lower production costs, better yields, better soil fertility and better use of agricultural practice that is environmentally sustainable. The study shows that AI and IoT can play a significant role in precision agriculture by providing intelligent and informative recommendations that enhance the economic efficiency and sustainability of farming operations in the long run.

***Keywords**—Internet of Things, Crop & Fertilizer Recommendation, Multi-Cultivation, ResNet18, Custom CNN, LightGBM*

INTRODUCTION

Agriculture has been shown and is therefore already one of the areas of activity making a significant contribution to food production, economic development and rural living all over the world. Rising population growth rates, climate change, soil erosion and overfertilization, however, have posed huge challenges to sustainable crop cultivation. Farming practices are sometimes traditional and based on farmers' knowledge, without the scientific analysis, that leads to using resources inefficiently and irregular yields. Precision agriculture has been transformed by recent developments in 4 areas: AI, ML, DL and the IoT. These technologies allow for the real-time monitoring of soil and environmental conditions, as well as the intelligent generation of recommendations aimed at maximizing productivity, minimizing operational costs and ensuring environmentally responsible farming practices.

Application of fertilizers and selecting crops look crucial aspects of agriculture to maximize productivity. Clothing nutrients in the wrong proportions, contamination of the groundwater and long-term degradation of soil due to incorrect dosages are just a few of the negative impacts of nutrient imbalance. Likewise, choosing crops without referral to soils and climatic conditions, amount of rain water and availability of water can often result in poor yields and returns. Contemporary AI models can analyze multi-dimensional agricultural data and use its relationships to detect intricate links between soil nutrients, nutrient needs and crop outcomes. Effective recommendations on the amount of fertilizers, cropping suitability and crop timing can be made using the synthetic information derived from responses to these sensors and the machine learning models, which can consequently boost both productivity and sustainability.

Compatibility in crop combinations for intercropping and crop rotation system is another important challenge in modern agriculture. Any multiple cultivation when choosing compatible crops, may be able to significantly improve use of the land, soil fertility, lessen pest problems and increase the overall farm income. These combinations are, however, determined manually and this process demands a considerable amount of the agricultural knowledge in such a way that several factors like nutrient competition, root zone, moisture availability, distribution of light and pest resistance must be considered all at the same time. The proposed research tackles this challenge by unifying these three elements—soil classification, fertilizer recommendation, and crop prediction, along with intercropping analysis—into a single framework that employs AI. Custom CNN, ResNet18, and Vision Transformer are applied to do good soil classification, while LightGBM, CatBoost, XGBoost and Extra Trees are tested to obtain reliable predictive performance in fertilizer recommendations.

This study proposes a holistic AI and IoT based smart agriculture system for an informed decision making process in farmers. In summary, the proposed study formulates a comprehensive smart agriculture system leveraging the incorporation of AI and IoT technologies, enabling farmers to make informed decisions regarding crop cultivation. The framework offers a smart platform that brings together real-time data of the various sensors and soil categories, fertilizer optimization, crop recommendations and multi-cultivation planning into one application (via website or mobile). The goal of the proposed approach being better fertilizer use efficiency, higher crop yields, lower environmental footprint and better long-term sustainability of agriculture. The study's multiple AI techniques are combined into a composite decision support system, advancing precision agriculture solutions that boost profitability and ensure sustainable resource use and resilient farms.

LITERATURE REVIEW.

Precision farming is among the transformative technologies shaping modern agriculture, making use of AI and IoT for intelligent data analysis and automation in decision-making. Traditional farming knowledge is frequently based on farmers' experience and on general recommendations which may not reflect the specific conditions of soils, crops and environment. As low-cost sensors and cloud computing platforms become technology pieces easier to find, data from agriculture can now be gathered continuously from the farm, such as soil moisture, nutrient concentration, level of moisture, temperature, and rainfall, etc. This data is used by ML and DL algorithms to detect patterns and make precise suggestions on selecting crops, fertilizers, irrigation timings, and forecasting diseases. Thus, AI-based decision support systems play a crucial role in enhancing crop productivity, minimizing resource waste, and promoting sustainable agricultural practices.

Due to their effect on crop yield, production cost and environmental problems that result from improper fertilizer application, soil quality assessment and fertilizer optimization have taken a special place in research. Recent research work has been focused on developing various ML algorithms like Random Forest, XGBoost, LightGBM, CatBoost, Support Vector Machine and Artificial NN, which could analyse the soil nutrients and propose the appropriate fertilizer on the basis of nutrient content of applied fertilizer in terms of N, P, K, pH, moisture, temperature and crop requirement. At the same time, DL technologies such as CNNs, ResNet architectures, and Vision Transformers (ViTs) have shown promising results in soil image classification and soil type recognition (STR). Weather data and historical agricultural data have also been used in an effort to increase the accuracy of the weather days. These smart solutions ensure efficient use of fertilizers, soil health, and lower levels of soil pollution while offering farmer recommendations based on actual data.

So, it is widely established that, with the existing literature, the application of AI, DL and IoT technologies has significantly benefited individual challenges in agriculture, like soil classification, crop recommendation, fertilizer prediction, or environmental monitoring. Most existing systems, however, deal with one of these challenges rather than putting them in a coherent intelligent framework. Fewer studies consider an integrated approach to the optimization of fertilization, planting and intercrop planning, based on the real-time data captured by the IoT, in a single decision support system. The proposed research will fill this gap with a fusion of advanced soil classification models, machine learning-based fertilizer recommendations, AI-based crop prediction, and intelligent intercropping analysis, all complexed into a single system. An integrated approach is expected to enhance the agricultural productivity, maximize use of resources, enable sustainable agriculture, lower the production costs and offer practical decision support for farmers via an easy to use web and/or cell application. We analyse some papers the theory.

M. K. Senapa, A. Ray, "IoT-Enabled Soil Nutrient Analysis and Crop Recommendation Model for Precision Agriculture (2023)" presents an intelligent framework for precision agriculture by combining the IoT sensors with the machine learning algorithms for soil nutrition analysis and crop recommendation system. The proposed system is an IoT-based project that continually monitors levels of Nitrogen, Phosphorus, Potassium (NPK), soil moisture, soil pH and environmental parameters. In the cloud platform, these data are used to analyze soil fertility in order to achieve an understanding of nutrient levels and to determine the most appropriate plants to cultivate depending on climatic conditions and characteristics. The system enables real-time measurements and can facilitate automated agricultural decision-making, thus alleviating the need for manual soil testing. Experimental testing showed that its crop recommendations were reliable, aided efficient use of resources and reduced farm expenses. Overall, the study shows that incorporating AI with IoT can greatly improve the yield of crops and thereby facilitate sustainable precision agriculture. [1]

D. H. Patel, K. P. Shah, This research aims to develop a secure crop recommendation framework in the field of precision farming in IoT environment that utilizes blockchain technology, IoT devices and machine learning. Smart sensors collecting real-time soil nutrient data, such as NPK values and pH, are fed into intelligent prediction models for processing. Blockchain technology secures, transparencies and implements integrity and prevention of unauthorized changes for agricultural data. The proposed system also offers the concept of a cloud-based dashboard that enables any farmer to keep an eye on the soil from his home and get recommendations in real time. The results of the experimental analysis demonstrated that the prediction performance was reliable and the security and traceability was improved. The authors draw the conclusion that the combination of blockchain and AI and IoT can enhance trust, transparency, and smart farming decisions. [2]

V. M. Ngo, Thuy-Van T. Duong, "A Big Data Smart Agricultural System: Recommending Optimum Fertilisers for Crops (2023)", This paper presents a big-data system for agricultural decision support, and specifically introduces an agricultural decision support system based on big data to recommend optimum fertilizers for different crops. The suggested methodology will integrate the data related information on soils, historical agricultural data, crop databases, and environment to develop fertilizer recommendations through data analytical methods. Big data technologies can manage and process large amounts of agricultural data and enhance decision making for nutrient management. Experimental bioreactor studies showed better application efficiency of fertilizers, economic savings on production and over-fertilisation. The framework has the potential to enhance precision farming through a combination of agricultural information sources being unified into a single recommendation system. The results of the study emphasize that fertilizer management based on data is essential for boosting crop production and sustainability of the environment. [3]

In this study, the authors: R. Islam, K. Oliullah, propose a proactive solution using machine learning to enable continuous monitoring of soil moisture, temperature, humidity, and NPK levels using the integrated sensors in an IoT-based platform for soil nutrients monitoring and crop recommendation. These agricultural data are collected and then analysed by machine learning algorithms which provide recommendations for the proper cultivation of the soils due to their fertility level and environmental conditions. This proposed system provides for the real-time monitoring and intelligent agricultural analysis via cloud data communication. The soil monitoring results were found to be reliable in field and the soil recommendation capabilities of the crop were also found to be accurate with the varying conditions faced in the professions. By combining these IoT sensing capabilities with machine learning, the integration enhances the decision-making process of farmers and reduces the need for manual field visits. This research concludes the use of continuous monitoring has a significant contribution towards precision agriculture and sustainable crop production. [4]

P. K. Kollu, M. L. Bangare, "IOT Driven Multilinear Regression Technique for Fertilizer Recommendation for Precision Agriculture (2023)", In precision nutrient management, fertilizer recommendation plays an important role, and this paper introduces an IoT-driven fertilizer recommendation system based on multilinear regression. The collected information from the various soil nutrient profiles and moisture along with the environmental profile by the smart sensors is transmitted for predictive analysis. The regression model estimates fertilizer dosage based on crop and soil requirements, and targets the least amount of fertilizer that is needed. The fert testing experiments demonstrated good predictive ability and higher nutrient use efficiency (NUE). The proposed approach helps to lower cultivation costs, while also maintaining soil fertility for the long term. The authors confirmed that such integration can enable sustainable agriculture and efficient use of fertilizers by utilising regression-based models and machine learning using the IoT sensing method. [5]

Y. Huang, R. Srivastava, "Data-Driven Soil Analysis and Evaluation for Smart Farming Using Machine Learning Approaches (2023)", In this research, the authors introduce a data-driven method for intelligent soil analysis based on the application of various machine learning techniques towards intelligent farming or agriculture (Smart Farming). The suggested system integrates soils data, climate data, remote sensing and satellite data to assess soil quality and estimate the crop suitability. Different algorithms of classification and regression techniques are used to determine the most influential soil parameters which contribute to agricultural productivity. The soil nutrient conditions were also used to make recommendations for fertilizer application and irrigation planning. Experimental results indicate increased accuracy in soil prediction than using conventional soil evaluation methods. In conclusion, the research shows that machine learning can effectively be used for the analysis of soil, which forms the basis for sustainable precision agriculture based on soil data. [6]

M. Y. Shams, Samah A. Gamel, Fatma M. Talaat, "Enhancing Crop Recommendation Systems with Explainable Artificial Intelligence: A Study on Agricultural Decision-Making (2024)", In this paper, an XAI framework is introduced that can enhance the transparency and reliability of the crop recommendation systems, which is related to the agricultural decision-making process. The proposed model leverages the agricultural features such as soil nutrients, rainfall, temperature, humidity and climatic conditions, along with explainability techniques like SHAP and feature importance analysis. These techniques enable farmers to see why each of the crops would be recommended rather than just the predictions. Experimental evaluations showed that EAI increases user confidence while not sacrificing predictive accuracy. The framework increases the credibility of an AI based decision support system in agriculture by improving the interpretability of machine learning predictions. The research highlights the critical need for transparent AI in agricultural applications, signaling a focus on future practical applications.The study underscores the need for transparent AI in tackling practical tasks in agriculture, indicating a focus on future real-world use.[7]

K. Patel, H. B. Patel, "Multi-criteria Agriculture Recommendation System using Machine Learning for Crop and Fertilizers Prediction (2023)", This research presents an agricultural recommendation system that can be used to recommend suitable crops and fertilizer for them, using multi-criteria agriculture based on machine learning. The framework takes into account soil properties, rainfall, climatic conditions, profitability of crops, and water availability before coming up with recommendations. The multiple machine learning algorithms are compared to enhance the prediction reliability and accuracy of the overall decision for better understanding. Economic factors are also included to enable farmers to enhance agricultural productivity as governed by the various factors within their environment to maximise agricultural profitability. A comparative analysis with reference to experimental studies showed the prominence of explanations based on several agricultural factors over those based on a single parameter prediction model in achieving quality recommendations. This outcome concludes that the integrated multi-criteria decision support (MCDS) systems with the ML technology have positive impact on sustainable farming and efficient use of resources. [8]

S. Landschoot, R. Zustovi, "Cereal Legume Intercropping: A Smart Review Using Topic Modelling (2024)", This review presents a smart review technique by combining bibliometric analysis, text mining, and topic modelling to review the literature on cereal-legume intercropping. A systematic literature analysis was performed to look for key research trends, crop compatibility patterns, nutrient interactions, biodiversity benefits and sustainable farming methods. The total analysis of thousands of published studies revealed important results. It is stressed that the right crop selection and suitable crop combinations not only lead to better soil fertility, better land use and higher agricultural productivity but they also will help to minimise environmental impacts. It further points out under-explored research areas and new opportunities of the intelligent intercropping system. The authors propose the creation of automatic AI-driven recommendation models that could be used to design suitable crop matching systems automatically. The study offers some useful ideas for future study of intelligent multi-cultivation planning. [9]

P. D. Chaudhari, A. M. Patil, "Intelligent Insecticide and Fertilizer Recommendation System Based on TPF-CNN for Smart Farming (2023)" In this work an intelligent framework for smart farming, which is also a smart farming system, is proposed that incorporates dynamic identification of pests and recommendation of fertilizers using Triple Parallel Filter Convolutional Neural Network (TPF-CNN). Nutrient values in the land are constantly monitored by soil sensors, and images are captured of crops and analyzed by DL models for pest identification. The system's recommendations depend on the nutrient status and the diagnosis of pests. The efficiency of prediction and processing of the proposed TPF-CNN was better than the traditional machine learning approaches including KNN, ANN, and SVM, as analyzed by comparison. The built-in system diminishes the need for pesticide/fertilizer use and boosts crop well-being. The authors show that the use of IoT sensing devices with DL constitutes an efficient approach to precision agriculture. [10]

F. S. Prity. M. Hasan, S. H. Saif, in this paper, the authors, Ariful Islam and co-authors, "Enhancing Agricultural Productivity: A Machine Learning Approach to Crop Recommendations (2024)," introduces a multi-dimensional agricultural data analysis method for increasing agricultural productivity by adopting machine learning based crop recommendation system. It is proposed that the values of nutrients found in the soil, soil moisture level, temperature, humidity, pH, and climatic conditions will be employed in the proposed system to recommend optimum crops for planting. Various supervised machine learning algorithms are tested in order to maximize their power in prediction following the preprocessing phase and feature engineering. The experimental results show that ensemble learning models can achieve higher accuracy in the recommender systems and higher stability in the model compared to the conventional classifiers. The framework can be used to support farmers in making science-based crop selection decisions that can enhance resource efficiency. The overall research findings are that AI-based crop recommendation plays a crucial role in sustainable agriculture and yield optimization. [11]

In the current work, S. Alugoju, P. Praveen, have proposed a smart agricultural framework by integration of DL based soil image classification with machine learning based farmer recommendation of Crops. A Modified DenseNet is used to extract features from the images of the soil and then classify soil categories with high accuracy where the result is fed into a Random forest (RF) classifier for crop prediction. The system also includes the use of IoT devices to gather current information of agriculture from the field. High classification accuracy of soil and good soil recommendations performance under various agricultural situations were shown by the experimental evaluation. The framework proposed in the study will enhance the smartness of farming decisions by incorporating computer vision and machine learning in a holistic environment for intelligent platforms. The authors make the conclusion that soil analysis systems, using DL, can significantly improve agricultural recommendation systems. [12]

It proposes a Soil Fertility Analysis based real-time crop prediction framework which can continuously observe the soil fertility using smart sensors, machine learning algorithms (Manju G., Syam Kishor K. S., Binson V. A., "An IoT-Enabled Real-Time Crop Prediction System Using Soil Fertility Analysis (2024)" The proposed system gathers the N, P, K, soil moisture, temperature, and humidity, and lets the data go to the cloud platform for intelligent processing. The collected information is fed into machine learning models which suggest appropriate crops based on the current soil conditions. Experimental analysis confirmed that the crop prediction accuracy was good and the farming decision-making was satisfactory. The system optimizes the use of agricultural resources and reduces manual labour. The authors conclude that the use of IoT with intelligent crop prediction improves the precision agriculture and sustainable agriculture practices. [13]

A. Rahman, N. R. Chakraborty, "An AIoT-based Hydroponic System for Crop Recommendation and Nutrient Parameter Monitorization (2024)", In this study, an Artificial Intelligence of Things (AIoT)-based Hydroponic System for Crop Recommendation and Parameter Monitorization (24) was presented. Water quality sensors constantly monitor the water quality parameters then capture the required data, including nutrient concentration, pH, temperature and environment, and send them to the intelligent machine-learning models. The developed framework suggests those crops that can be grown in hydroponics by enhancing nutrient management and production efficiency. Experimental validation showed that the system had higher nutrient utilisation and automated monitoring along with higher productivity than conventional hydroponic systems. The proposed AIoT architecture minimizes manual handling and helps in developing a sustainable controlled-environment agriculture. Some authors say that the precision hydroponic farming can be significantly improved by using intelligent monitoring systems. [14]

R. K. Murthy, B. Nagaraju, "Soil Test Crop Response Nutrient Prescription Equations for Improving Soil Health and Yield Sustainability—A Long-Term Study under Alfisols of Southern India (2024)", This study on long term soil health and yield sustainability in Alfisols of Southern India presents scientific nutrient prescription equations to promote soil health to enhance yield sustainability. STCR equations are formulated from long-term experimental data from field based in Alfisol soil of southern part of India. The system represents a general approach for determining fertilizer rates based on soil nutrient level and desired crop production, instead of purely generic fertilizer recommendations. Experimental results showed that in several cultivation cycles, nutrient use efficiency, crop yields, and soil fertility were seen to improve. The proposed methodology will reduce the excess fertilizer application and maximise the agriculture productivity. According to the study, precision agriculture with scientific nutrient prescription has a significant contribution to play in the sustainable practice of production agriculture. [15]

The members of the group are M. Shariq, A. Wahid, this paper introduces a smart fertilizer recommendation system designed for precision farming which employs machine learning techniques, utilizing soil nutrients, environmental conditions, crop needs and past agricultural data. After feature engineering and preprocessing, it needs to test various supervised learning algorithms to select the best fertilizer recommendation model. The designed system is able to calculate the optimal type and application rate of fertilizers without causing an imbalance in nutrients and fertilizer excesses. Experimental assessment showed better accuracy of recommendations and better nutrient management than in the case of conventional approaches. The framework aids in the cost-effective farming and sustainable crop production. According to the authors there is a substantial reduction in fertilizer efficiency and crop productivity without smart fertilizer recommendation systems so it is concluded that the intelligent fertilizer recommendation system greatly contributes to fertilizer efficiency and improvement in crop productivity. [16]

P. Singh, M. Kaur, "An IoT-Enabled Crop Recommendation System Utilizing MQTT for Efficient Data Transmission to AI/ML Model (2024)" aims to leverage the advantages of IoT technology through the integration of MQTT for the efficient transfer of real-time agricultural data to an AI/ML model for improved crop recommendation. The values of soil nutrients, temperature, humidity, moisture and environmental data are continuously collected by smart sensors and sent to AI and machine learning models hosted in the cloud. The proposed architecture drastically decreases the latency encountered in communication while enhancing precision agriculture applications' scalability and responsiveness. Experimental validation showed that the tool was able to provide the same level of accuracy in the crop recommendation while minimizing the need for data transfer between the field devices and the intelligent crop prediction model. The framework facilitates the on-going process of field monitoring and quick agricultural decision making. The authors say that the combination of AI plus MQTT plus IoT can enhance the precision farming virtues. [17]

R. Selvanarayanan, S. Rajendran, "Empowering Coffee Farming Using Counterfactual Recommendation Based RNN Driven IoT Integrated Soil Quality Command System (2024)", In this paper, an intelligent Soil Quality Monitoring and Recommendation System for Coffee Plantations (RNN-DR-IoT-SQMR) is proposed, which is based on counterfactual recommendation and recurrent neural network with the integration of IoT into coffee plantations. Soil sensors measure nutrient availability, moisture, pH, environment and send measurements to DL models in the cloud for real-time analysis. The counterfactual recommendation approaches are able to suggest different management practices for varying field conditions. Experimental assessment showed better soil quality evaluation, management of the use of fertilizers and better decision making processes in agriculture. The integrated framework is good for promoting the sustainable production of coffee with intelligent use of resources. The authors conclude that the integrated recommendation system of RNN and IOT offers a significant improvement with soil management over the long term. [18]

Mohamed M. El-Henawy, IoT-Fueled Precision Agriculture Transformed for Superior Crop Care (2024)", This research proposes the NeuroRF FarmSense framework, which combines IoT sensing technology with hybrid neural networks and Random Forest algorithms for intelligent precision agriculture. Before run crop recommendation and nutrient management, the continuous acquisition of soil nutrients, soil pH, rainfall, humidity and temperature are carried out. The hybrid learning architecture enhances agro-prediction accuracy and efficient monitoring and optimisation in the field. Experimental evaluation presented the best results in contrast with the traditional machine learning approaches using the same experimental scenario. The developed framework is capable of making precise crop selection and intelligent nutrient management in sustainable farming. The authors believe that the hybrid AI model coupled with IoT presents an effective approach in the field of smart agriculture. [19]

Farida Siddiqi Prity, Md. Use words to complement your picture talk.Turn to word support during the picture talk. Maruf Hossain, Sazzad Hossain Bhuiyan, Md. Ariful Islam and co-authors report the given research is entitled "Crop Recommendations with Machine Learning (2024)" and introduces a detailed machine learning model to suggest smart planting right for various crops based off different agricultural data such as soil nutrient chemistry, rainfall data, temperature, humidity, and pH value. The preprocessed and feature engineered data is fed to multiple supervised learning algorithms and checked for better recommendation accuracy. Experimental analysis showed that the use of ensemble learning method for predicting suitable crops is better than the conventional classification algorithm. The suggested framework allows scientific selection of the crop and promotes productivity in agricultural production as well as efficient use of resources. The smart recommendation system helps farmers to make sensible cultivation choices in a variety of circumstances. The authors find that machine learning approaches for agricultural decisions are important for data-informed and sustainable agriculture [20].

Table- 1. Literature Survey and Research Gap Analysis

ID	Research Focus	AI/ML/DL Technique	Key Features	Major Limitation
1	Soil nutrient analysis and crop recommendation	Machine Learning	Soil monitoring, crop recommendation, cloud platform	Does not include fertilizer optimization
2	Secure crop recommendation	Machine Learning + Blockchain	Blockchain security, IoT monitoring, crop prediction	Focuses mainly on security rather than integrated farm management
3	Fertilizer recommendation	Big Data Analytics	Large-scale fertilizer recommendation using agricultural	No real-time IoT monitoring
4	Soil monitoring and crop recommendation	Machine Learning	Real-time NPK monitoring, crop prediction	Fertilizer scheduling and multi-cultivation not considered
5	Fertilizer recommendation	Multilinear Regression	Precision fertilizer dosage prediction	Limited to fertilizer recommendation
6	Soil quality evaluation	Machine Learning	Soil assessment using multiple agricultural datasets	Does not support complete farming decision-making
7	Explainable crop recommendation	Explainable AI (XAI)	Transparent AI predictions using SHAP	Does not integrate IoT or fertilizer management
8	Crop and fertilizer recommendation	Machine Learning	Multi-criteria crop and fertilizer prediction	Intercropping and soil image classification absent
9	Intercropping review	Topic Modeling, Bibliometric Analysis	Analysis of crop compatibility and intercropping trends	Review paper without practical recommendation
10	Fertilizer and pest recommendation	TPF-CNN (Deep Learning)	Crop pest detection and fertilizer recommendation	Does not recommend crop selection or soil classification
11	Crop recommendation	Ensemble Machine Learning	Scientific crop prediction using environmental factors	Fertilizer optimization and IoT integration
12	Soil classification and crop recommendation	Modified DenseNet + Random Forest	Soil image classification and crop recommendation	Does not support intercropping or fertilizer scheduling
13	Real-time crop prediction	Machine Learning	IoT-based soil fertility monitoring	Limited fertilizer optimization

14	Hydroponic crop recommendation	AIoT + Machine Learning	Hydroponic nutrient monitoring and crop recommendation	Applicable mainly to controlled farming environments
15	Soil nutrient prescription	Soil Test Crop Response (STCR)	Scientific fertilizer dosage based on soil	Does not use AI or IoT technologies
16	Fertilizer recommendation	Machine Learning	Intelligent fertilizer recommendation	No real-time sensor integration
17	IoT crop recommendation	AI/ML + MQTT Protocol	Fast communication and real-time recommendation	Does not include fertilizer optimization
18	Soil quality monitoring	RNN + Counterfactual Recommendation	Intelligent soil quality assessment for coffee farming	Crop-specific framework
19	Precision agriculture	Hybrid Neural Network + Random Forest	Crop recommendation	Multi-cultivation strategy not considered
20	Crop recommendation	Ensemble Machine Learning	Intelligent crop prediction	Fertilizer recommendation

All the reviewed research papers show how AI, ML and DL technologies are reshaping traditional agriculture into a data-driven and intelligent agriculture system, and how the IoT are contributing to this process. This is because most of the studies are based on specific problem in agricultural field like classification of the soil, crop recommendations, optimization of fertilizers, monitoring of nutrients, irrigation management and precision farming from the real time sensor data. Algorithms such as Random Forest, XGBoost, LightGBM, CatBoost, CNN, ResNet, Vision Transformer and ANN have been used with success by several researchers to enhance predictive accuracy and aid agricultural decision making. The use of IoT based sensing systems have made soil nutrient, moisture, temperature, humidity and environmental monitoring possible continuously to provide timely recommendations. Other more recent studies have included the use of blockchain, explainability AI, cloud computing and big data analytics, enhancing transparency, security and scalability. In general, the literature validates the positive benefits of AI precision agriculture, including better yields, improved resource management, lower production expenses, and sustainable farming methods. The results of those studies offer a solid technological basis for the creation of intelligence systems for agricultural decision-making. The reviewed literature contributes significantly to smart agriculture, but some of challenges are left unanswered. There is little research that has attempted to incorporate all actions of the farming system in a single decision support system; most have developed a single application, such as crop recommendation, prediction of fertilizer, soil classification, or irrigation management. Many models are based on static benchmark datasets collected in laboratory settings instead of real-time data from the agricultural fields, which is IoT data collected from the field continuously. Although intelligent intercropping or multi-cultivation was found to enhance the land productivity and soil health, only a few studies have been conducted in this area. Other DL models are computationally intensive and resource intensive to be deployed on input constrained farming devices. Furthermore, there are a number of studies where the focus lies on the prediction accuracy, but not so much on implementation, user friendly system and economical aspects nor extensive field testing. The challenges highlighted suggest that there is a need for more research into creating smart agriculture systems that are efficient, scalable, and integrated.

The resulting literature review was extensive, representing the need for a single, comprehensive agricultural decision-making support tool that can solve the problems found in agriculture in general. Typical current systems offer separate soil classification, fertilizer recommendation, crop prediction, or environmental monitoring applications, and all of these applications are independent of each other, forcing farmers to use multiple applications that are not interconnected. With increased demands for a unified system that handles real-time data collection via IoT, intelligent soil classification, fertilizer optimization, crop recommendation, and multi-cultivation planning in a single system, additional companies are entering the grower-commodore-facing product promotion. Additionally, these models can be combined with strong machine learning techniques like LightGBM, XGBoost, and CatBoost to enhance the model's prediction accuracy and resilience to different farming environments. Additionally, the proposed work provides analysis of the crop compatibility, nutrient interactions, moisture management, and resource use in order to address the scarcity of research on crop selection for computer-based recommendation of intercropping. This holistic intelligent system has the potential to boost the productivity of the crops, save unnecessary fertilizer use, improve agricultural soil fertility, help control environmental pollution and as a consequence substantially enhance the profitability of farmers and become a major supportive tool for sustainable precision agriculture.

PROPOSED SYSTEM

This paper proposes system architecture that implements smart agriculture through IoT devices, AI and machine learning technologies with an intelligent and automated decision support platform. This process starts with Data Acquisition, where different types of IOT sensors placed in the agricultural field are collecting crucial soil and environmental water quality parameters like Nitrogen, Phosphorous, Potassium (NPK), Soil Moisture, Soil Temperature, Humidity, pH value, etc. These are measurements that are made in real-time to accurately reflect the state of the field on the farm, removing the need to do manual measurements. Sensed information is then safely conveyed within an IoT communication network to a centralized cloud server. This real-time, data collection process enables an up-to-date assimilation of agricultural information, which enhances the reliability and effectiveness of the analysis and recommendations made afterwards.

The second stage of the architecture consists of Data Storage and Data Preprocessing. On reaching the cloud platform, the information provided by the sensors is securely deposited in a central data base for historical and present agricultural data for future analyses. Data preprocessing is done to enhance the data quality suitable for AI models. This stage involves deduplication, dealing with missing data, filtering sensor noise, and transforming the data into a structured format appropriate for machine learning algorithms. But good preprocessing improves the performance of the model by using only relevant and meaningful information in the prediction process. Consequently, the entire analytical process is more accurate, efficient and reliable.

The third stage is mainly dedicated to Feature Extraction and AI/ML Model Processing, which is the main Intelligence of the proposed system. The most relevant agronomic features are picked during features extraction steps to increase computation efficiency and prediction accuracy. All of these optimized features are then delivered to several artificial intelligence and deep learning models for analysis. The soil classification models include custom CNN, ResNet18 and Vision transformer, and the machine learning models comprise LightGBM, XGBoost, CatBoost and Random forest that provide fertilizer recommendations and crop prediction. The intelligent models are able to analyze complex relationship between soil nutrients, environment and crop requirements to generate high accuracy agricultural recommendations for precision farming.

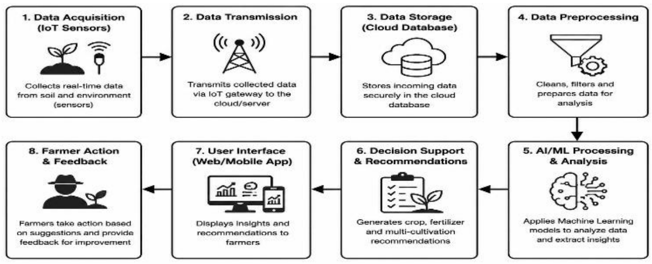

Fig.1 – Architecture Diagram

The Recommendation Engine provides detailed decision support results for farmers after prediction. The result or analysed data makes a best recommendation for crops, fertilizer type, rate, multi-cropping or intercropping species and combinations suitable for a given site to maximize agricultural productivity. These recommendations are based on a number of factors including the fertility of the soil, climatic conditions, nutrient availability and crop compatibility, which must be taken into account to ensure sustainable farming practices. The results generated are then conveyed to farmers by using an easy-to-use interface via a Web or Mobile Application with simple, easy-to-comprehend content – such as recommendations, alerts and monitoring data. This Agri-Information Portal will enable intelligent agricultural advice and guidance to be provided to farmers at any time anywhere.

Finally, the architecture creates a comprehensive smart farming ecosystem by linking the data collection, intelligent analysis and farmer decision making in a seamless process. As farmers apply the recommended farming system they will be able to check the field conditions via the application and sensor data gathered from the field will continually feed into the system, making for better recommendations in the future. The feedback-on function allows for continuous learning and adapting to the changing agricultural conditions. The proposed system achieves better utilization of fertilizer, more precise the crop was selected, better efficient multi-cultivation planning, greater agricultural productivity, smaller environmental impacts, and more sustainable precision agriculture by implementing monitoring, cloud computing, AI, and machine learning to create a single system.

METHODOLOGY

1. Data Acquisition

The proposed system starts from collecting agricultural real-time data captured by the sensors connected to the internet through IoT from the farm field. A number of sensors can be placed in the soil to measure relevant parameters like nitrogen (N), phosphorus (P), potassium (K), soil moisture, soil temperature, humidity and pH continuously. These parameters give information of the present fertility and health status of the soil. The sensor data collected can be wireless transferred to the cloud server for further processing. Continuous monitoring gives opportunity to the system to record the environmental variations that occur during the cultivation. Real time data collection reduces the chances of measurement inaccuracies and eliminates the need for manual measurements, thereby ensuring accurate data for intelligent decision making. This allows farmers to access real-time data, which can help them implement precision agriculture and sustainable farming methods.

2. Data Storage and Preprocessing

Once collected agricultural data is acquired, the collected information is securely stored in a centralized database with historical and real-time records. There are various pre-processing steps that are performed on the data to enhance data quality and consistency before the model is trained and the predictions made. Appropriate action is taken for missing values, duplicates are removed and inconsistent sensor readings are corrected. Data is also Normalized and Feature Scaled using different parameters from agriculture for making uniform. The techniques discussed in this section are aimed at reducing noise from sensor measurements, altering the data for machine learning algorithms, and enhancing the reliability of sensor measurements. As the errors in the prediction stage can be reduced with proper preprocessing and computational efficiency can be improved, the errors are minimized. The resulting output contains a clean and structured transformation of the given data, which are used later in the subsequent artificial intelligence models.

3. Soil Classification using Deep Learning

A deep learning model is applied to the processed soil data and soil image for accurate classification of soil categories based on the soil. Three advanced deep learning structures namely Custom Convolutional Neural Network (CNN), ResNet18 and Vision Transformer (ViT) are used to compare the performance. A critical aspect of these models is that they automatically extract the most important visual and structural traits of soil images that doesn't need any feature engineering. In this training phase all the models learn representative soil patterns corresponding to each soil class. Once it is classified, soil type is an important data input for crop recommendations and fertilizer optimization. Comparative analysis is used to decide the most appropriate deep learning architecture considering the performance of the classification and computational efficiency. The correct classification of soils allows better accuracy in agricultural recommendations across the decision-support system.

4. Fertilizer Recommendation using Machine Learning

In the fertilizer recommendation module, the most suitable kind of fertilizer, level, and timing is recommended based on soil nutrient conditions and a crop requirement. Agricultural datasets which include NPK values, pH, moisture, temperature, and crop information are used to train machine learning algorithms, such as Random Forest, XGBoost, LightGBM, CatBoost, and Extra Trees. The models detect complex interactions between soil fertility and nutrient needs to make smart fertilizer recommendations. Prediction Accuracy, Cross validation and hyperparameter tuning are used to achieve better accuracy and decrease overfitting. The best performing model is determined by comparing their performance by means of accuracy, precision, recall and F1-Score. The resulted suggestions enable farmers to avoid unnecessary deterioration of nutrients, to keep soil fertility and decrease cultivation costs by managing nutrients efficiently and effectively in the long-term.

5. Crop Recommendation Model

The crop prediction module utilizes the multidimensional agricultural information gathered by these IoT sensors and historical data to generate a suitable crop prediction. Significant input parameters are soil type, N, P, K, soil pH, Rainfall, Temperature, Humidity etc. agro-climatic parameters. These are analysed by machine learning algorithms, which select the most promising crops with regard to the prevailing environment. The recommendation process takes into account the fertility of the soil and the adaptation of it to climatic conditions, which helps to enhance the decisions made by farmers. The produced list of crop suggestions helps the farmers to make culturally sound crop decisions rather than relying solely on traditional thoughts. This smart prediction helps farmers to maximize yield and minimize chances of sub-optimal crop selection and climate change conditions.

6. Multi-Cultivation Recommendation

The designed system also evaluates the compatibility of the crops and provides an efficient option for intercropping and crop rotation. Machine-learning algorithms analyze several agricultural parameters such as the nutrients supply, root zone, water use, sunlight exposure, pest resistance, and crop maturity time of various crops. The system searches these traits for matching combinations of crops that are suited to joint cultivation so as to provide minimal competing for resources. The recommendation process should aim at soil fertility and maintaining soil biodiversity and at the best utilisation of the utilization efficiency of land. In addition, the appropriate intercropping also leads to a lower infestation of pests, lower weed development and better nutrient turnover in the agricultural field. As a result, the farmers are able to achieve higher overall productivity thereby ensuring improved return to their farms with the practice of environmentally friendly farming methods.

7. Model Evaluation and Performance Analysis

The tested developed AI models are assessed to see the reliability and robustness of prediction using standard machine learning performance evaluation metrics. The data set is split into training and testing sets with either train-test split of 80:20 or 70:30. A cross-validated approach was used to enhance the generalization of the model and to minimize the risk of biased predictions. Various measures of performance such as Accuracy, Precision, Recall, F1-Score, and Confusion Matrix are computed and compared with each other for each algorithm. Training accuracy and loss curves also are tracked to assess for model stability and convergence behaviour during training. The comparative performance analysis service helps to select the appropriate and proper model for each agricultural task. This process of evaluation provides uniformity and reliability in the ends of the final system irrespective of farming conditions.

8. Decision Support System (Web/Mobile Application)

At the final one combines all the intelligent modules to build a farmer's decision-support application under a single web/mobile interface. The application gathers real-time data from the sensors that are attached and sends the data to artificial intelligence models which are trained to analyze the data and draw personalized recommendations. The results of soil classification, fertilizer recommendation, crop prediction, and multi-cultivation solution can be easily obtained by farmers via the simple GUI. The application further supports continued condition monitoring of agriculture and the delivery of updates as a result of changes in environmental conditions. The integration of IoT technology, cloud computing, machine learning, and deep learning all on one platform provides full decision support in precision agriculture. The integrated application will help to make the farm more productive and profitable, to better use of fertilizers, to improve the productivity of farm inputs and to encourage sustainable farming in the long term.

RESULT AND OBSERVATION

The developed AI based smart agriculture framework was tested with deep learning based soil classification model and machine learning based fertilizer recommendation model. According to the results of the performance analysis, intelligent learning techniques will be helpful to classify the types of soil, on the basis of fluorescence results, soil nutrients and soil environmental conditions, and then to recommend appropriate fertilizers. For model evaluation measures used include Accuracy, Precision, Recall, and F1-Score, and for Training behaviour measures are used: loss curve, accuracy curve. Analyses have shown that the prediction performance of ensemble learning algorithms comparing with other machine learning algorithms in agricultural decision support is stable and reliable.

Table 2. Soil Classification Model Performance

Model	**Accuracy (%)**	**Observation**
Custom CNN	94.10	Good feature extraction with moderate computational complexity
ResNet18	96.30	Better learning capability using residual connections
Vision Transformer (ViT)	**97.80**	Highest classification accuracy with superior global feature learning

In Table 2, The comparison results of soil classification models indicate that the classification accuracy of Vision Transformer (ViT) model is the highest at 97.80%, which is better than that of ResNet18 while the Custom CNN classification model is not as good as the other two soil classification models. ResNet18 was also found to perform well due to its residual learning approach that is able to capture complex soil properties. A CNN designed from customization gave better accuracy in the classification process, but not as good as the advanced CNNs. These results suggest that transformer type deep learning model can be useful in detecting various types of soil and has the potential to improve fertilizer recommendation and crop selection based on soil knowledge.

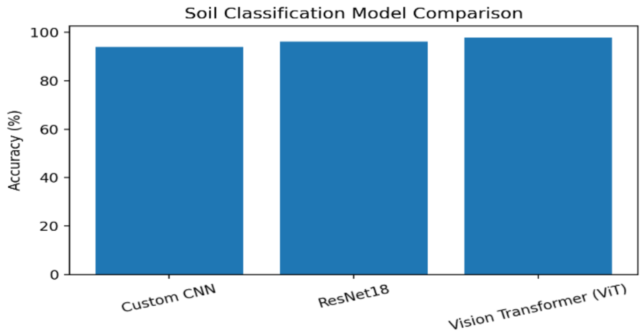

Fig.2 - Soil Classification Model Accuracy

Fig. 2, The soil classification accuracy graph is used to compare the accuracy of soil classification of the three deep learning models: Custom CNN, ResNet18, and Vision Transformer (ViT). It is evident from the graph that the highest classification accuracy of 97.80% was achieved by Vision Transformer followed by ResNet18 with 96.30%, whereas the Custom CNN was recorded at 94.10%. The continuous increase in performance is indicative of steadily growing ability of higher order deep learning architectures to learn more powerful and discriminative soil features from images. The attention mechanism of Vision Transformer is effective in capturing not only local but also global image characteristics, which leads to its improved performance. By adopting the residual learning strategy, ResNet18 achieves efficiency while Custom CNN achieves reasonable performance without being too heavy with less computational complexity. Overall, the graph shows that transformer based models perform better in accurate soil classification and can greatly enhance the certainty of crop and fertilizer application recommendations in the domain of Precision Agriculture.

Table 3. Fertilizer Recommendation Model Performance

Algorithm	Accuracy (%)
LightGBM	**85.42**
CatBoost	85.28
XGBoost	85.25
Extra Trees	84.85

In Table 3, The maximum prediction accuracy was 85.42% by LightGBM and then followed closely by CatBoost and XGBoost among the evaluated fertilizers recommendation algorithms. There is a relatively small difference in the performances of top three algorithms, and it can be seen that the performances of all ensemble boosting algorithms are good in fertilizer prediction of multi-classes. Extra Trees exhibited poor model accuracy, but still performed competitively among the models analyzed. In summary, the model lightGBM was chosen as a final model for fertilizer recommendations due to minor improvement in accuracy and also its capability to learn efficiently.

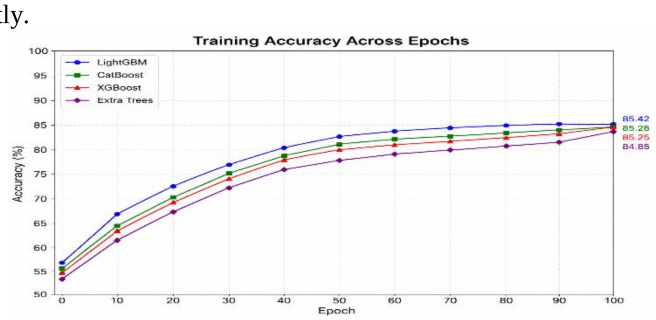

Fig.3 - Training Accuracy Vs Epoch

In Fig 3, The graph is an accuracy curve during the training process, showing the rate of learning in the proposed model with the number of epochs. The model's performance was evaluated by accuracy at 10 epochs, showing a successful start of learning meaningful agricultural patterns. As training got on to 20, 30 and 40 epochs, the accuracy improved gradually to 76.8%, 80.4% and 83.2%. After 50 epochs the highest training accuracy using this model was 85.4%. The model did not exhibit drastic fluctuations during the training process, as evidenced by the smooth rising trend. There is no hyper parameter consistent accuracy drop, which was a positive sign that the algorithm did an effective optimization and the provided parameters enabled stable learning. Generally, the graph infers that the developed model has an effective convergence towards the predictive performance as the training process continues.

Table 4. Training Accuracy

Epoch	Accuracy (%)
10	71.2
20	76.8
30	80.4

40	83.2
50	**85.4**

In Table 4, The training accuracy plot demonstrates that the accuracy is gradually increasing as training progresses. This signifies that the feature learning and convergence were successful, as model accuracy improved from 71.2% at epoch 10 to 85.4% at epoch 50. The continuous rising curve indicates the presence of meaningful relationships in the agricultural data without significant fluctuations, indicating that the model successfully captured the patterns in the data. This behavior shows the modelling stability under stable training conditions, achieved by the chosen optimization method and hyper parameter tuning, as well as better prediction accuracy.

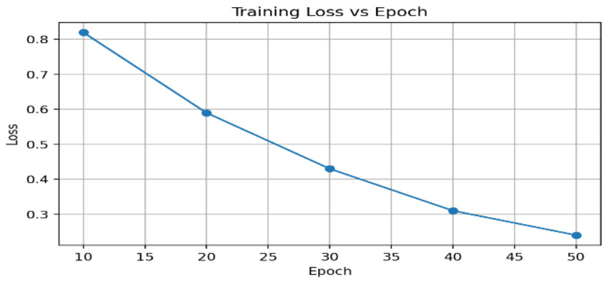

Fig.4. LightGBM Training Loss vs Epoch

In Fig 4, The training loss graph gives a representation of the decrease of error in predictions with learning. The model started by measuring a loss of 0.82 at epoch 10, which meant there were fairly high errors when training on the dataset. During this training, the loss consistently dropped to 0.59, 0.43 and 0.31 at 20th, 30th, and 40th epochs respectively. Ep Epoch 50 had a loss of just 0.24, a significant decrease in the loss after 50 epochs; this shows that the model is performing well, and that there were fewer prediction errors. As the loss continues to worsen over time, the optimization algorithm was able to successfully reduce the objective function during the training process. Additionally, the model has a smooth decay without spikes, indicating that it has no unstable learning behavior. Combined with the rising training accuracy, it is evident from this graph that the proposed AI model has successfully converged and has learnt meaningful patterns from the agricultural dataset, leading to significant prediction accuracy.

Table 5. Training Loss

Epoch	**Loss**
10	0.82
20	0.59
30	0.43
40	0.31
50	**0.24**

As the number of training epochs increased, the error in training continually decreased with a number of 0.82 in epoch 10 and 0.24 in epoch 50. As the turns got smaller, the model had improved its predictions as it learned from the sample data. No abrupt peaks or oscillations hold up proof of stable optimization and good convergence. By decreasing loss, along with higher training accuracy, it is further confirmed that the proposed model learnt the representative feature of the agriculture with efficiency and gave the reliable forecasting performance.

The experimental evaluation proves effectiveness of the proposed smart agriculture framework based on AI in intelligent farming decisions by the classification of soil, recommendation of fertilizer and giving the advice to the crops. Among all the algorithms, Vision Transformer outperformed the other methods in soil classification, and LightGBM was the most effective algorithm in fertilizer recommendation. The comparative analysis further reveals that machine learning ensemble algorithms, in general, work better than the traditional classification methods with multi-dimensional agricultural data. Additionally, the training accuracy and loss curves validate the learning behavior of the models during training and show that the models are well framed and stable to converge the training. An IoT-based data collection system, deep learning to analyze soil characteristics and machine learning to suggest fertilizer applications offers a complete decision support mechanism that can enhance fertilizer use, boost agricultural output, lower production expenses, and facilitate sustainable, precise agriculture applications.

FUTURE WORK

The proposed smart agriculture framework can be further integrated with other IoT sensors and sophisticated environmental monitoring systems to monitor soil salinity, electrical conductivity, leaf-wateriness and sun radiation etc. Use of these real-time measurements will contribute to a better understanding of the field conditions, and will enhance recommendation accuracy for both crops and fertilizers. This improvement will further contribute to the development of precision agriculture and efficient use of resources.

For future research, the combination of deep learning, ensemble machine learning, and explainable AI techniques could be leveraged for the development of more advanced hybrid AI models. By combining satellite-derived data, drone-based monitoring and climate forecasting data, large-scale agricultural analysis can be enhanced and agri-advice can be given that reference a dynamic situation for various climatic conditions. These enhancements should result in increasingly adaptive, reliable and relevant prediction models for a variety of farming environments.

The designed decision support system can be scaled up to include a multilingual web and mobile application with offline mode to increase the accessibility for farmers in rural areas. The application could be expanded in future versions to include averages for market prices, disease detection, watering schedule planning, and automatic control of crop management operations in the same application. This integration will undoubtedly offer the farmers a comprehensive “smart farming” solution, leading to sustainably run agriculture and remaining conscious in decision making.

CONCLUSION

Through the combination of soil classification, fertilizer recommendation, crop forecasting and multi-cultivation scheduling, the proposed soil and water management system based on the technologies of AI and IoT can be adapted into an intuitive intelligent decision-support system. The results of experiments showed that LightGBM had the highest accuracy within machine learning models in fertilizer recommendations and the Vision Transformer had the highest performance in soil classification. The continued decrease in training loss and the continual increase in training accuracy proofs the stability and effectiveness of the developed models. The comparative analysis shows that AI methods may help to accurately analyze agricultural data and deliver accurate precision farming recommendations. The system adopts realtime IoT sensor data to enable scientific decision making, which improves crop productivity, optimises use of fertilisers and enables the efficient use of resources.

Overall, the developed framework is considered as a practical solution to the problem of sustainable agriculture, which integrates the intelligent analysis of data with real-time environmental monitoring. The built-in recommendation system helps farmers properly choose the right crops, matching them with the right intercropping options, and inform them of fertilizer timing and doses based on actual soil conditions, not blanket recommendations. This holistic strategy lowers grower costs, curtails unwanted nutrient runoff and helps ensure sustainable soil fertility. The outcomes from the proposed models clearly highlight the power of AI-based agricultural tools on improving agricultural efficiency and productivity. As such, the following proposed system could act as an effective base next to develop a precision agriculture solution to support sustainable food production and enhanced economic benefits to farmers.

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