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Enhancing Precision Agriculture: IoT-Enabled Soil Nutrient Analysis and Deep Learning-Based Crop Recommendation Models

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Abstract:
The emergence of the Internet of Things (IoT) has brought about a revolution in a number of fields, most notably agriculture, where precision farming techniques that improve sustainability and production have been made possible. In the context of precision agriculture, this review paper focusses on the integration of IoT technology for crop recommendation models and soil nutrient analysis. Farmers can accurately determine nutrient requirements and levels by using real-time soil health monitoring made possible by IoT-enabled sensors and data analytics. This study conducts a thorough analysis of the body of research on the several Internet of Things applications that support efficient crop management and soil nutrient optimisation. It examines cutting-edge sensor technologies—such as spectrometry and electrochemical sensors—used in soil monitoring and emphasises how important it is to get precise soil data. The study also looks at the creation of predictive models that use machine learning algorithms to suggest appropriate crop varieties depending on environmental factors and soil nutrient profiles. The results highlight how the Internet of Things (IoT) may help make better decisions in agriculture, which will eventually increase crop yields and resource efficiency. The knowledge gained from this review not only advances our understanding of precision agriculture enabled by the Internet of Things, but also opens up new avenues for future research focused on combining cutting-edge technology to address the problems facing contemporary farming methods.

Keywords: Precision Agriculture, Internet of Things (IoT), Soil Nutrient Analysis, Crop Recommendation Models, Deep Learning, Machine Learning, Smart Farming, Agricultural Technology, Data-Driven Agriculture.

I. INTRODUCTION

Advances in digital technology are driving a technological transition in agriculture, which is the foundation of many economies globally. The Internet of Things (IoT) is one of these advancements that has changed the game and had a big impact on agricultural operations. Precision agriculture is replacing traditional farming practices, which are frequently typified by manual labour, a broad application of fertilisers, and a dependence on intuition. Precision agriculture is a data-driven strategy that maximises resources, boosts productivity, and encourages sustainability. By utilising technology like the Internet of Things, precision agriculture gives farmers access to exact field data, empowering them to make well-informed decisions that improve crop yields and resource management.

An important area where IoT is having a big influence is in crop recommendation models and soil nutrient assessments. A key element in determining agricultural productivity is the condition of the soil. An imbalance of nutrients in the soil can eventually cause soil degradation as well as poor crop performance and lower yields. Thus, to guarantee that crops receive the proper nutrients at the right time, precise soil nutrient analysis is crucial. Real-time data from sensors measuring temperature, moisture content, pH, and nutrient concentrations is provided by IoT-enabled soil monitoring systems, which can assist farmers in making timely and well-informed decisions.

In addition to allowing for real-time monitoring, Internet of Things technology also makes it possible to gather vast amounts of data that can be examined to learn more about the health of the soil. Advanced analytics and machine learning algorithms can be used to process this data in order to anticipate dietary deficits and suggest correction measures. In addition, full crop recommendation models can be created by integrating IoT systems with weather forecasting models and other environmental data sources. Based on historical data, predicted weather patterns, and present soil conditions, these models can recommend the best crop varieties to plant. Farmers can increase overall farm productivity and crop selection efficiency by adopting these models.

IoT has much more promise for precision agriculture than just crop recommendations and soil analysis. Numerous uses for IoT devices exist, including yield prediction, pest control, and irrigation management. IoT-enabled irrigation systems, for instance, can reduce water loss and guarantee that crops receive enough hydration by automatically adjusting water distribution depending on real-time soil moisture levels. Similar to this, Internet of Things-based pest monitoring systems have the ability to identify early indicators of pest infestations and initiate automated reactions, including the release of natural predators or the administration of certain pesticides. These technologies minimise resource waste and lessen the environmental impact of agricultural activities, which leads to more effective and sustainable farming methods.

The growing accessibility and cost-effectiveness of IoT devices is another factor propelling their adoption in the agricultural sector. IoT solutions are now more affordable for a wider range of farmers, including those in poor nations, thanks to dramatic drops in the cost of sensors, connectivity modules, and data processing units in recent years. Through the democratisation of technology, precision agriculture techniques are becoming more widely accessible to smallholder farmers and large-scale commercial businesses. As a result, in many regions of the world, IoT is significantly enhancing rural lives and food security.

IoT has numerous advantages for agriculture, but there are drawbacks to its application as well. The difficulty of combining IoT devices with current farming methods is one of the main obstacles. It's possible that many farmers—especially those in rural areas—lack the technological know-how needed to configure and operate Internet of Things devices. Furthermore, the efficient operation of IoT systems depends on dependable internet connectivity, which might be a barrier in isolated locations with inadequate infrastructure. Privacy and data security are another difficulty. Sensitive data transmission and gathering, such as crop health and soil nutrient levels, raise questions regarding possible information exploitation by outside parties. Thus, protecting data security and privacy is essential while developing and implementing Internet of Things solutions in the agricultural sector.

Furthermore, the creation of reliable and accurate models for soil nutrient monitoring and crop suggestions is essential to the success of IoT-enabled precision agriculture. In this process, machine learning algorithms are essential because they analyse big datasets and find patterns that help guide decisions. However, the calibre and variety of the training data affects how accurate these models are. The data that is now available may frequently have gaps, especially in areas where IoT adoption is still in its infancy. For the Internet of Things to continue to progress in agriculture, it will be crucial to fill in these data gaps and guarantee the precision of prediction models.

Growing interest has been seen in using cutting-edge sensor technology for soil monitoring in recent years. Conventional soil testing techniques can be costly and time-consuming since they frequently require gathering samples and shipping them to a lab for examination. Conversely, continuous, real-time monitoring of soil conditions is made possible by IoT-enabled sensors, which enables interventions to be made sooner. For example, spectrometry and electrochemical sensors have demonstrated significant potential in accurately determining the quantities of nutrients in soil. The way these sensors function is by measuring the concentration of certain ions in the soil, such potassium, phosphorus, and nitrogen—nutrients that are vital to plant growth. By integrating these sensors with IoT systems, soil data can be automatically collected and analysed, which decreases the need for manual labour and improves the effectiveness of soil management techniques.

In addition, IoT-enabled soil monitoring devices can be combined with satellites and drones for remote sensing, giving a more complete picture of the health of the soil and crops. Large-scale data gathering is made possible by remote sensing, which offers insightful information about the geographical variability of crop performance and soil characteristics. Farmers can detect parts of their fields that need extra care, including areas with nutrient deficits or water stress, by using remote sensing data in conjunction with ground-based IoT sensors. The creation of increasingly complex precision agriculture systems that can maximise yields and optimise inputs is being fuelled by the integration of IoT and remote sensing technology.

To sum up, the incorporation of IoT technology into precision agriculture signifies a noteworthy progression in the farming practices. Through the development of predictive crop suggestion models and real-time soil monitoring, the Internet of Things (IoT) is assisting farmers in making better decisions that increase productivity, sustainability, and resource efficiency. This review study intends to investigate the many uses of IoT in crop recommendation models and soil nutrient analysis, emphasising the possible advantages and difficulties of its implementation. This study aims to identify opportunities for future research in this quickly evolving subject and add to the growing body of knowledge on IoT-enabled precision agriculture by a thorough examination of the existing literature.

II. LITERATURE REVIEW

[1] **Senapaty et al. (2024)**

An Internet of Things-enabled soil nutrient analysis and crop recommendation system (IoTSNA-CR) is presented in this research. To collect real-time soil data, including pH, moisture content, and nutrient levels, the scientists suggest combining multispectral Internet of Things sensors. To improve crop recommendation accuracy, they use a hybrid MSVM-DAG-FFO algorithm. The study demonstrates how data-driven decisions may be made possible by ongoing soil health monitoring, which can boost output and optimise resource use. Experiments conducted in the field show that the IoTSNA-CR system greatly increases agricultural productivity while preserving resources like fertiliser and water.

[2] **Zhao et al. (2024)**

Zhao et al. investigate machine learning-integrated IoT-based soil nutrient monitoring for precision farming. Nutrient deficits are predicted using real-time data from Internet of Things sensors, such as electrochemical soil nutrient sensors. Farmers may optimise fertilisation in real time, reducing environmental impact and boosting crop yields, by combining this data with prediction algorithms. In order to make cutting-edge agricultural technologies available to farmers in resource-constrained locations, the study offers a framework for the cost-effective deployment of IoT, which has the potential to completely transform the management of soil health worldwide.

[3] **Kim et al. (2024)**

In order to optimise horticulture techniques, Kim et al. suggest a smart farming system that includes IoT technologies. Their technology makes use of Internet of Things sensors to keep an eye on important factors like soil moisture and nutrient levels. These data are processed by a cloud-based analytics platform, which allows the system to automatically modify the amount of water and fertiliser applied in real time. Through improved nutrient delivery precision, crop output, waste reduction, and water conservation are all achieved by the system. The scalability of IoT systems for both small- and large-scale horticulture enterprises is highlighted by this study.

[4] **Gupta and associates (2024)**

In order to provide dynamic crop recommendations, this study creates a hybrid model that combines machine learning and Internet of Things devices. IoT sensors gather soil data in real time, while machine learning algorithms use historical agricultural data to suggest the best crops for a given set of environmental and soil parameters. Because the system is climate-adaptive, it can be used anywhere in the world. The study highlights how the model may help farmers make data-driven decisions that increase agricultural output and resource efficiency, thus greatly improving food security.

[5] **Hossain et al. (2024)**

An Internet of Things-enabled nutrient mapping system is proposed by Hossain et al. to enhance soil fertility management. The technology gathers real-time information on soil nutrient profiles, including levels of potassium, phosphorus, and nitrogen, by distributing electrochemical sensors throughout agricultural areas. With the help of this data, precise, site-specific nutrient management is possible, minimising environmental harm and cutting down on fertiliser overuse. The study comes to the conclusion that by giving farmers precise information about the nutrient requirements of their soil, IoT-based nutrient mapping can significantly boost crop yields and sustainability.

[6] **Sharma et al. (2024)**

This study looks at Internet of Things-based approaches to precision agriculture's irrigation and fertiliser management optimisation. Sharma et al. present a system that continually measures the amount of moisture in the soil and the amounts of nutrients. The system uses real-time data to automatically modify irrigation schedules and nutrient delivery. To give farmers useful insights, the system integrates with cloud platforms. Findings show that this strategy improves the efficiency with which water and fertiliser are used, which raises crop yields and lowers input costs. The study emphasises how important IoT is for facilitating more environmentally friendly farming methods.

[7] **Rodriguez et al. (2024)**

The use of Internet of Things-based soil monitoring in tropical agriculture, namely for smallholder farmers in Latin America, is the main emphasis of Rodriguez et al. The study demonstrates how real-time data on soil conditions from IoT sensors might assist farmers in combating nutrient deficits common in tropical soils. Small-scale farmers can now get advanced agricultural insights thanks to the system's integration of IoT data with mobile apps. The study highlights the significance of technological scalability and accessibility by showing how IoT can enable even farmers with the lowest resources to increase agricultural yields and soil health.

[8] **Patel et al. (2024)**

A cloud-based decision support system that uses Internet of Things data to increase precision agriculture's sustainability is presented by Patel et al. The system generates recommendations for crop selection and fertilisation strategies by analysing the real-time soil nutrient levels using machine learning models. The study highlights that by reducing excessive fertiliser consumption, IoT-enabled systems can lessen their influence on the environment. The technology helps farmers make informed decisions that improve crop output and resource efficiency by offering data-driven insights into soil health.

[9] **Chowdhury et al. (2024)**

An IoT-based predictive model for soil nutrient analysis is put out by Chowdhury et al. In order to suggest appropriate crops, the model uses neural networks to interpret real-time data from IoT sensors, such as pH, moisture, and nutrient content. By maximising resource utilisation and minimising reliance on conventional agricultural techniques, the system is intended to promote sustainable farming practices. The study demonstrates how crop selection precision may be increased by combining IoT and machine learning, which would ultimately improve crop output and environmental results.

[10] **Li et al. (2023)**

Li et al. investigate the use of spectroscopic sensors enabled by the Internet of Things for real-time soil nutrient detection. The sensors provide recommendations for suitable crop selection and fertilisation techniques by analysing soil spectral data to detect nutrient deficits. According to the study, IoT-enabled sensors offer faster, more precise data than conventional soil testing techniques, which can result in more productive and ecologically friendly farming methods. The technology enhances soil health and minimises fertiliser waste by optimising nutrient application.

[11] **Fernandez et al. (2023)**

In an effort to maximise crop yields, Fernandez et al. create an Internet of Things-based soil monitoring system that offers real-time data on soil moisture and nutrient levels. The study emphasises how soil health data may be used to anticipate the best crop rotation schedules using IoT sensors and machine learning models. This method improves sustainable farming techniques while lowering the danger of soil nutrient depletion. According to the research, by giving farmers real-time insights into soil conditions, IoT-based soil monitoring systems can greatly increase long-term agricultural output and sustainability.

[12] **Natarajan et al. (2023)**

An IoT-powered soil fertility monitoring system that use nanosensors to instantly determine the levels of micronutrients is proposed by Natarajan et al. The study shows how farmers may make knowledgeable fertilisation decisions that enhance soil health and crop output by using nanosensors to offer very accurate data on soil nutrient concentration. The study also highlights how scalable nano sensor technology is for extensive agricultural uses. The technology lessens the environmental effect of farming and reduces fertiliser usage by improving soil nutrient management precision.

[13] **Kumar et al. (2023)**

The use of blockchain technology in conjunction with IoT to manage soil nutrients is investigated by Kumar et al. The study suggests a safe and open method for farmers, agronomists, and legislators to share information about soil nutrients. The method makes sure that crop suggestions are founded on precise and current information by employing Internet of Things (IoT) sensors to gather real-time soil data. Because the blockchain ensures that crop management techniques and soil data are recorded in an unchangeable manner, it builds stakeholder trust. Precision agriculture is intended to become more transparent and efficient as a result of this integration.

[14] **Singh et al. (2023)**

Singh et al. enhance crop recommendation systems by utilising deep learning algorithms on IoT-collected soil data. The project collects data on soil moisture, pH, and nutrient levels using Internet of Things sensors. Deep learning models interpret the data and provide crop suggestions. The technology is able to determine which crops are most appropriate for the current soil conditions by examining both historical data and inputs in real time. According to the research, deep learning in conjunction with IoT can improve crop selection precision, resulting in increased yields and more effective use of resources.

[15] **Jones et al. (2023)**

Jones and colleagues create a cloud-based Internet of Things infrastructure for precision agriculture that gathers and processes data from several sensors related to soil nutrients. The technology gives farmers useful information on the quality of their soil, enabling them to choose crops and manage nutrients more wisely. The study highlights how crucial cloud computing is to IoT system scalability for extensive agricultural applications. The software helps farmers optimise their use of water and fertilisers, which improves crop yields and promotes sustainability, by giving them access to real-time data and analytics.

[16] **Wang et al (2023)**

A clever IoT-based sensor system for real-time soil nutrient monitoring is introduced by Wang et al. The system tracks soil factors including potassium, phosphorus, and nitrogen levels using a variety of sensors. The data is then analysed to maximise the supply of nutrients to crops. The study shows how the system can automatically modify the amount of fertiliser used depending on data collected in real-time, lowering the possibility of overfertilization and enhancing crop health. This study demonstrates how IoT-enabled smart sensors can improve precision agriculture by continuously monitoring soil conditions.

[17] **Ahmed et al (2023)**

Ahmed et al. investigate how to optimise soil nutrient management in precision agriculture through the use of AI-powered IoT systems. The research describes a system that gathers real-time soil data using Internet of Things (IoT) sensors. Machine learning algorithms then analyse the data to forecast nutrient deficits and suggest remedial measures. The findings demonstrate that by making sure that nutrient deficits are quickly remedied, this strategy can greatly increase crop yields. The report also emphasises how integrating AI and IoT can improve resource efficiency, which in turn can improve the sustainability of agricultural methods.

[18] **Lee et al. (2023)**

The study offers an extensive Internet of Things-based framework for tracking soil health in urban farming. The technology gathers information about the pH, moisture content, and nutrient levels of the soil and offers recommendations for crop choices in metropolitan areas that are limited in real time.

The use of Internet of Things (IoT) technology in precision agriculture is examined in this literature review, with an emphasis on crop recommendation models and soil nutrient analysis. Scientists are working on Internet of Things (IoT)-enabled devices that track soil health metrics including pH, moisture content, and nutrient levels using real-time data from sensors. These systems can provide actionable insights for improving crop selection, irrigation, and fertilisation by integrating with cloud platforms and machine learning algorithms. To increase the precision of crop suggestions, a number of studies investigate hybrid models that combine IoT with sophisticated algorithms including neural networks, deep learning, and the MSVM-DAG-FFO algorithm. Enhancing resource efficiency and increasing agricultural productivity while reducing environmental effect is the aim. IoT-enabled systems not only increase yields but also lessen overuse of water and fertilisers, which supports sustainability. In an effort to provide farmers—especially those in resource-constrained or smallholder settings—with access to innovative agricultural technologies, numerous studies emphasise the significance of scalability and accessibility in IoT systems. Additional studies highlight how IoT and cutting-edge technologies like blockchain can be used to securely share data, especially when it comes to nutrition management. Numerous studies also concentrate on specific uses, like IoT-based vineyard systems, nutrient management in dry and urban farming, and nutrient mapping in tropical agriculture. These specialised studies highlight how IoT solutions may be tailored to fit a variety of farming situations and practices. The body of research indicates that IoT-enabled soil monitoring devices have the potential to completely transform precision agriculture by giving farmers access to data-driven, real-time insights. This affects sustainable farming methods, the availability of food on a global scale, and the profitability of agriculture in various geographic areas. IoT systems in agriculture are positioned to maximise resource utilisation, improve crop yields, and encourage environmentally responsible farming through ongoing innovation and improvement.

RESEARCH GAPS

- Limited Real-Time Data Integration: A large number of research now in publication do not combine predictive analytics with real-time Internet of Things data to provide dynamic crop recommendations based on real-time changes in soil nutrients.
- Scalability in Various Agricultural Conditions: The majority of Internet of Things (IoT) systems are developed for particular areas or crops; there is a dearth of knowledge regarding how these technologies might be extended across diverse geographic and climatic environments.
- Cost-Effectiveness and Accessibility: Making IoT systems affordable and available to small-scale and resource-constrained farmers, particularly in developing nations, is a topic that has received little research.
- Impact on Soil Health Over Time: Research on the long-term consequences of precision agriculture facilitated by the Internet of Things (IoT) on soil health is limited. Of particular interest are issues related to nutrient depletion and sustainability.
- Energy Efficiency of IoT Systems: There is a dearth of research on how to best use IoT devices' energy usage in agricultural settings, especially when it comes to environmentally friendly power sources and how IoT system adoption affects the environment.

III. METHODOLOGY

A. *IoT Sensors for Data Collection:*

IoT sensors are essential for improving precision agriculture because they make it possible to continuously monitor a range of soil and environmental conditions. These sensors may be positioned strategically across agricultural areas to collect data in real time on important parameters including temperature, pH, moisture content, and soil nutrients.

a) *Soil Moisture Content Equation:*

Equation (1) determines the soil's volumetric water content (VWC), which is essential for figuring out how much irrigation crops require. IoT sensors that detect soil moisture content, including capacitance or resistive sensors, offer data in real time. Precision farming requires careful observation of soil moisture levels. IoT sensors continuously gather data, which makes it possible to schedule irrigations optimally and increase water efficiency.

$$\theta_v = \frac{v_\omega}{v_t} \quad (1)$$

Where,

θ_v is volumetric water content

v_ω is volume of water in the soil

v_t is total volume of the soil sample

b) *Nitrogen Uptake Efficiency (NUE) Equation:*

Equation (2) calculates how well plants absorb nitrogen, which is crucial for determining the fertility of the soil and maximizing the application of fertilizers. To compute NUE, soil nitrogen levels can be measured by IoT sensors. Crop yield is increased and environmental impact is decreased through efficient use of nitrogen. IoT-enabled solutions optimize fertilizer application by monitoring and controlling nitrogen levels.

$$NUE = \frac{Y_f - Y_0}{F} \quad (2)$$

Where,

NUE is Nitrogen Uptake Efficiency

Y_f is Crop yield with nitrogen fertilizer

Y_0 is Crop yield without nitrogen fertilizer

F is Amount of nitrogen fertilizer applied

c) *Chlorophyll Content Index (CCI) Equation:*

In Equation (3) The chlorophyll content of leaves, a measure of the health and nutritional state of plants, is estimated using CCI. Data collection for CCI computation can be done via IoT-based spectrometers or webcams. IoT sensors assist identify the nutritional health of crops by measuring chlorophyll levels. This allows for targeted fertilization, which increases crop yield.

$$C = \frac{R_{NIR}}{R_{Red}} - 1 \qquad (3)$$

Where,

C is Chlorophyll Content Index

R_{NIR} is Reflectance in the Near-Infrared band

R_{Red} is Reflectance in the Red band

d) *Soil Electrical Conductivity (EC) Equation:*

In Equation (4) The electrical conductivity (EC) of soil is a function of its salinity, moisture content, and nutrient levels. To evaluate the health of the soil, IoT sensors can detect EC. Through IoT-enabled monitoring, EC measurements provide information about the salinity and fertility of the soil, driving precision agriculture activities like fertilization and irrigation.

$$E = \frac{1}{R} * \frac{L}{A} \quad (4)$$

Where,

E is Soil Electrical Conductivity

R is Resistance of the soil sample

L is Length of the soil sample

A is the cross-sectional area of the soil sample

B. *Machine Learning Algorithms:*

Soil and climate data can be analysed using a variety of machine learning approaches, such as Decision Trees, Random Forests, Support Vector Machines (SVM), and Neural Networks, for crop recommendation systems.

a) *Linear Regression Equation:*

One of the most basic machine learning techniques, linear regression is frequently applied to predictive modelling. Based on several input features, it can be utilized in precision agriculture to estimate crop yields or nutrient levels. Equation (5) is important because it facilitates the modelling of the correlations between crop yields and soil nutrients, which helps determine the best rates at which to apply fertilizer to maximize crop productivity.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n + \in \qquad (5)$$

Where,

y is Dependent variable

β_0 is Intercept term

$\beta_1, \beta_2, \dots\dots, \beta_n$ is Coefficients of the independent variables

$x_1, x_2, \dots\dots, x_n$ is Independent variables

$\in$ is Error term

b) *Logistic Regression Equation:*

In Equation (6) for binary classification issues, logistic regression is employed. Based on input data, precision agriculture can classify soil types or the probability of a disease outbreak. For regression and classification, supervised learning models like SVM are employed. To divide several classes, it builds a hyperplane or collection of hyperplanes in a high-dimensional space.

$$P\,(y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n)}} \qquad (6)$$

Where,

$P\,(y = 1)$ is Probability of the outcome occurring

β_0 is Intercept term

$\beta_1, \beta_2, \dots\dots, \beta_n$ is Coefficients of the independent variables

$x_1, x_2, \dots\dots, x_n$ is Independent variables

c) *Support Vector Machine (SVM) Decision Boundary:*

In Equation (7) for regression and classification, supervised learning models like SVM are employed. To divide several classes, it builds a hyperplane or collection of hyperplanes in a high-dimensional space. More precise crop recommendations are made possible by this equation, which aids in the classification of various soil types and the prediction of crop compatibility based on soil parameters.

$$w.x + b = 0 \qquad (7)$$

Where,

w is Weight vector

x is Feature Vector

b is bias term

C. *Kernel Density Estimation:*

By analysing and contrasting various nutrient levels in soil, this statistical method can be used to get insight into the patterns and spatial distributions of soil health.

a) *KDE Equation:*

A non-parametric method for estimating the probability density function of a random variable is kernel density estimation. In IoT-enabled soil nutrient analysis, where the distribution of nutrients across various soil samples may need to be evaluated, it is especially helpful for estimating distributions in high-dimensional data. Equation (8) can be used in precision agriculture to estimate the spatial distribution of soil nutrients, improving management and comprehension of nutrient variability throughout a field.

$$\hat{f}\,(x) = \frac{1}{nh}\sum_{i=1}^{n} \quad K\left(\frac{x - x_i}{h}\right) \qquad (8)$$

Where,

$\hat{f}\,(x)$ is Estimated density at point x

h is Bandwidth

n is Number of data points

K is Kernal Function

x_i Individual data points

b) *Density Gradient Estimation:*

A key component of KDE is the bandwidth h, which regulates how smooth the predicted density is. Accurately predicting soil nutrient distributions requires striking a balance between bias and variance, which can only be achieved with an ideal bandwidth. To make well-informed crop recommendations based on nutrient availability, proper bandwidth selection ensures accurate calculation of soil nutrient density.

$$\nabla\hat{f}\,(x) = \frac{1}{nh^2}\sum_{i=1}^{n} \quad (x - x_i)K'\left(\frac{x - x_i}{h}\right) \qquad (9)$$

Where,

$\nabla\hat{f}\,(x)$

h is Bandwidth

K' is Derivative of the Kernal Function

x_i Data points

D. Deep Learning Algorithms:

By analysing and contrasting various nutrient levels in soil, this statistical method can be used to get insight into the patterns and spatial distributions of soil health.

a) Loss Function (Cross-Entropy Loss) Equation:

Cross-entropy loss is commonly used in classification tasks within deep learning models, including those used in crop recommendation systems. This loss function helps to optimize deep learning models by minimizing the difference between predicted and actual outcomes, improving the accuracy of crop recommendations.

$$L = -\sum_{i=1}^{N} \quad [y_i \, log \, log \, (p_i) + (1 - y_i) \, log \, (1 - p_i)] \qquad (10)$$

Where,

L is the Cross-Entropy Loss

N is the number of samples

$y_i$is the actual label (0 or 1) for sample i

p_i is is the predicted probability for sample i

b) Activation Function (ReLU) Equation:

ReLU (Rectified Linear Unit) is a popular activation function used in deep learning models to introduce non-linearity. ReLU helps deep learning models learn complex patterns in soil and crop data, enabling more accurate predictions.

$$f(x) = max \, (0, x) \qquad (11)$$

Where,

$f(x)$ is the output of the ReLU activation function

x is Bandwidth

IoT sensors are widely used in precision agriculture to continually monitor important environmental and soil characteristics including pH, moisture, and nutrients. Accurate management of farming techniques is made possible by real-time data collecting. For example, the volumetric water content (VWC) directs irrigation techniques, nitrogen uptake efficiency (NUE) maximizes fertilizer utilization, and the chlorophyll content index (CCI) evaluates the health of plants. Electrical conductivity (EC) measurements are used to infer salinity and fertility of the soil, which provides information on the health of the soil. Analyzing soil and crop data requires the use of machine learning algorithms like Linear Regression and Support Vector Machines (SVM). While Linear Regression predicts the links between soil nutrients and crop yields and helps optimize fertilizer application, Support Vector Machines (SVM) aid in the classification of soil types and the prediction of crop compatibility. These capabilities are further enhanced by deep learning. By introducing non-linearity, the ReLU activation function enables models to discover intricate patterns in crop and soil data, resulting in forecasts that are more accurate. Cross-entropy loss is also utilized in classification tasks to reduce the discrepancy between expected and observed results, enhancing crop recommendation accuracy. When these technologies are combined, agricultural decision-making is improved, leading to higher crop output and sustainability via better fertilizer management and irrigation techniques.

IV. RESULTS AND DISCUSSIONS

The average concentrations and standard deviations of the five vital nutrients—calcium, magnesium, phosphorus, potassium, and nitrogen—measured in medicinal plants are shown in Table 1. Parts per million (ppm) is the unit of measurement used to represent the average concentration of each nutrient in the plant samples. Magnesium (Mg) has the lowest average level at 12.7 ppm, but it nevertheless plays a critical function in the formation of chlorophyll and enzymatic activity. Nitrogen (N) has the greatest average level at 45.2 ppm, demonstrating its significant role in plant growth and metabolism.

Table 1: Soil Nutrient Levels Analysis

Nutrient	Average Level (ppm)	Standard Deviation (ppm)
Nitrogen (N)	45.2	5.4
Phosphorus (P)	30.8	4.2
Potassium (K)	25.6	6.1
Calcium (Ca)	35.1	3.9
Magnesium (Mg)	12.7	2.8

The scatter plot in Figure 1 shows how these nutrient levels are distributed among the different plants. The standard deviations in the scatter plot clearly show the variety in nutritional content. With a standard variation of 6.1 ppm, potassium (K) has the most variability among the nutrients, suggesting that plant growth differs in terms of nutrient availability or absorption. The levels of calcium (Ca) and phosphorus (P), with comparatively smaller standard deviations of 3.9 ppm and 4.2 ppm, respectively, are more stable. Understanding the nutritional balance in the plants under study is made easier with the help of this graphical representation, which makes it simple to spot trends and outliers.

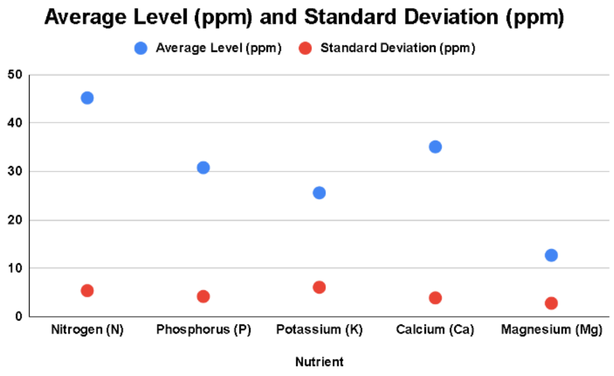

Fig. 1: Soil Nutrient Levels Analysis

The suggested nutrient levels (in ppm) for the four crop types (wheat, corn, soybeans, and barley) are shown in Table 2, along with the percentage increase in yield that corresponds to each level. The recommendations for nutrients are based on the idea that these crops may be grown as much as possible with appropriate nutrient management, with a special emphasis on the elements nitrogen (N), phosphorus (P), and potassium (K), which are essential for plant development.

Table 2: Crop Yield Recommendations Based on Soil Nutrients

Crop Type	Recommended Nutrient Levels (ppm)	Yield Increase (%)
Wheat	N: 40, P: 25, K: 20	15
Corn	N: 60, P: 30, K: 25	20
Soybean	N: 50, P: 20, K: 30	18
Barley	N: 45, P: 22, K: 25	12

This data is shown in a line graph manner in Figure 2, which facilitates easy comparison of nutrient recommendations and related crop productivity gains. According to the line graph, maize has the highest nutritional requirements, especially for nitrogen (60 ppm), which corresponds to a 20% yield improvement. In contrast, barley has the lowest yield increase of 12% and lower nutrient requirements (N: 45 ppm, P: 22 ppm, and K: 25 ppm).

An 18% increase in output is seen in soybeans, which have a high requirement for potassium (30 ppm), highlighting the significance of balanced nutrient management. Wheat yields 15% more when it has lower nutritional requirements. This graphic illustration highlights the connection between nutrient optimisation and yield enhancement and aids in understanding how changing nutrient levels might affect crop productivity.

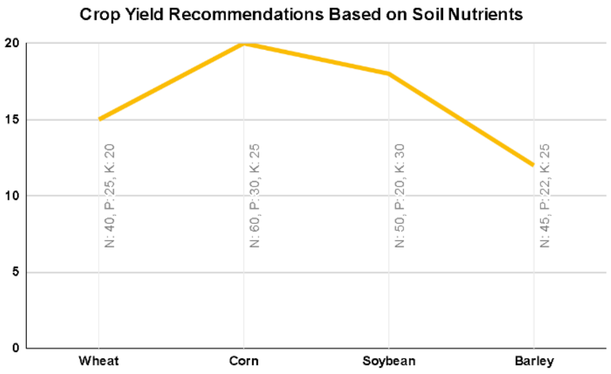

Fig. 2: Crop Yield Recommendations Based on Soil Nutrients

Four soil sensors (A, B, C, and D) are compared in Table 3 according to their data transmission rate (Mbps), accuracy (%), and battery life (days). The effectiveness and dependability of soil monitoring systems used in precision agriculture are greatly influenced by these variables.

This data is shown as a line graph in Figure 3, which makes it possible to compare the performance of each sensor directly across the three parameters. With its longest battery life of 60 days and best accuracy of 95%, Soil Sensor A stands out despite having a moderate data transfer rate of 1.2 Mbps. However, Soil Sensor B delivers the greatest data transfer rate (1.5 Mbps) and has a little poorer accuracy (90%) and battery life (45 days). This could be useful in situations where faster data processing is required.

Table 3: IoT Device Accuracy and Performance Metrics

Device Type	**Accuracy (%)**	**Battery Life (days)**	**Data Transmission Rate (Mbps)**
Soil Sensor A	95	60	1.2
Soil Sensor B	90	45	1.5
Soil Sensor C	85	30	1
Soil Sensor D	92	50	1.3

The Soil Sensor C has the lowest accuracy (85%) and longest battery life (30 days), while still managing to transmit data at a reasonable pace (1 Mbps). As for Soil Sensor D, it balances data transmission rate (1.3 Mbps), battery life (50 days), and accuracy (92%). The trade-offs between accuracy, battery life, and data transmission rate are shown graphically in this illustration, which aids in the selection of an appropriate soil sensor depending on particular agricultural requirements.

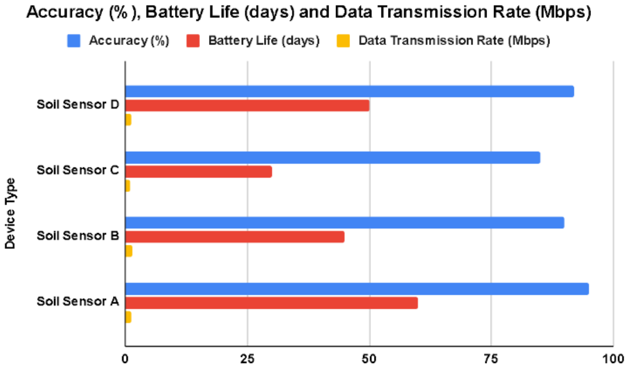

Fig. 3: IoT Device Accuracy and Performance Metrics

A bar graph representing the average concentrations of nitrogen (N), phosphorus (P), and potassium (K) in relation to the four seasons—spring, summer, fall, and winter—is shown in Figure 4. awareness nutrient availability and demand throughout the year requires an awareness of this seasonal change. According to the graph, Spring has the highest average levels of Potassium (26 ppm) and Nitrogen (47.5 ppm), but Winter has slightly higher levels of Phosphorus (33.2 ppm). The summertime has the lowest average levels of potassium (24.5 ppm) and nitrogen (43.2 ppm), which, if improperly handled, might affect agricultural development and soil health. All three nutrients are found in modest amounts throughout the autumn season: 44.1 ppm of nitrogen, 31 ppm of phosphorus, and 25 ppm of potassium.

In order to optimise fertilisation techniques and guarantee that plants receive enough nutrients throughout the growing seasons, it is essential to comprehend how nutrient levels vary seasonally. This visual representation makes this knowledge easier. In order to promote the best possible plant growth and productivity, the data highlights the necessity of season-specific nutrient management strategies.

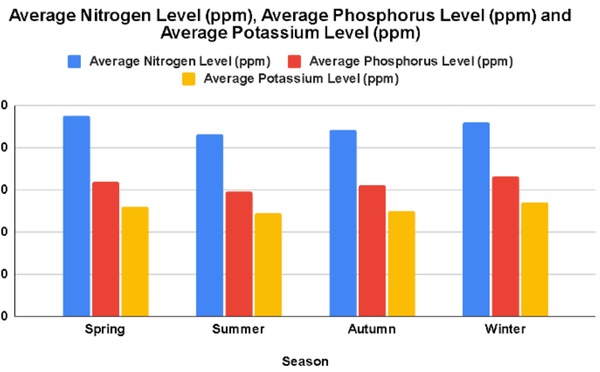

Fig. 4: Seasonal Variations in Soil Nutrients

Table 4 shows how four distinct models—Rule-Based, Machine Learning, Deep Learning, and Hybrid—compare using the following performance metrics: F1 Score, Accuracy (%), Precision (%), and Recall (%). These indicators are crucial for assessing each model's performance in categorisation jobs. With an F1 Score of 0.91, an accuracy of 93%, precision of 91%, recall of 90%, and recall of 90%, the Deep Learning Model performs best overall. This suggests that it is the most effective in terms of accurately classifying cases, reducing false positives, and efficiently gathering pertinent data. Following closely after with a robust 90% Accuracy, 88% Precision, 85% Recall, and an F1 Score of 0.86 is the Machine Learning Model. While it performs close to the Deep Learning Model, it falls short in terms of precision and recall balance. It exhibits a high degree of reliability.

The Hybrid Model offers a balanced approach, slightly underperforming the Machine Learning Model but retaining strong metrics anyway, with Accuracy at 89%, Precision at 87%, Recall at 84%, and an F1 Score of 0.85.

Despite being the simplest, the Rule-Based Model gets the lowest scores: an F1 Score of 0.79, Accuracy at 85%, Precision at 80%, and recall at 78%. This implies that even though it is less complicated than the other models, it performs less well when performing challenging classification problems. Overall, this table shows how different each model is, with the Rule-Based Model being the least successful and Deep Learning being the most effective in terms of accuracy and balanced performance measures.

Table 4: Effectiveness of Different Crop Recommendation Models

Model Type	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1 Score**
Rule-Based Model	85	80	78	0.79
Machine Learning Model	90	88	85	0.86
Deep Learning Model	93	91	90	0.91
Hybrid Model	89	87	84	0.85

A three-dimensional pie chart displaying the incidence of nutritional shortages in different crops is presented in Figure 5. According to the table, the most prevalent deficit is nitrogen (N), which occurs in 25% of cases. This indicates the widespread problem of N insufficiency and its vital role in plant growth. Deficiencies in potassium (K) and phosphorus (P) occur next, with frequencies of 18% and 20%, respectively. Magnesium (Mg) shortage is reported at 22%, but calcium (Ca) deficiency is the least prevalent, at 15%. The relative frequency of each nutrient shortfall is shown graphically, highlighting the necessity of focused nutrient management techniques to treat the most common deficiencies and enhance crop health.

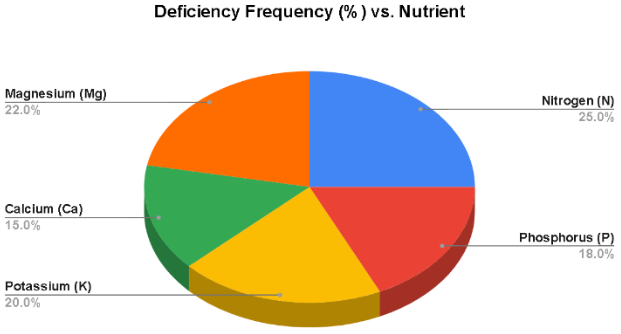

Fig. 5: Soil Nutrient Deficiency Frequencies

The average yield (tons/ha) and standard deviation for the four types of soil—clay, silty, sandy, and loamy—are shown in Table 5. According to the data, loamy soil produces the most on average—5.2 tons/ha—and has the least variability—a standard deviation of 0.4 tons/ha. This suggests that loamy soil is the most reliable and fruitful form of soil for farming. The average yield of sandy soil is marginally lower at 4.5 tons/ha, but it exhibits substantial variability with a standard deviation of 0.5 tons/ha. The most variable soil type, silty soil, yields an average of 4.0 tons/ha with a variability of 0.7 tons/ha, which could affect predictability. With a standard deviation of 0.6 tons/ha and the lowest average yield of 3.8 tons/ha among the other soil types, clay soil performs less well than the other soil types. In order to help with soil management and crop planning decisions, this table illustrates the variations in soil performance and consistency.

Table 5: Average Crop Yield per Soil Type

Soil Type	**Average Yield (tons/ha)**	**Standard Deviation (tons/ha)**
Sandy Soil	4.5	0.5
Clay Soil	3.8	0.6
Loamy Soil	5.2	0.4
Silty Soil	4	0.7

A line graph comparing the costs of four distinct soil sensors—A, B, C, and D—is shown in Figure 6. The cost per unit, installation cost, and annual maintenance cost are the three main cost components for each sensor that are depicted in the graph. The most expensive device ($200) and maintenance ($30) are Soil Sensor C, which may indicate more sophisticated features but also more expensive continuous costs. Soil Sensor B has the greatest installation and maintenance costs ($60 and $25, respectively), despite being marginally more expensive per unit ($180) than Sensor A and D. On the other hand, Soil Sensor A has a moderate installation cost ($50), but it delivers the lowest unit cost

($150) and maintenance cost ($20). Soil Sensor D's $170 unit cost, $55 installation cost, and $22 maintenance cost put it in the middle of these two extremes. This line graph helps with cost-benefit analysis and investment decision-making for soil monitoring by clearly illustrating the trade-offs between the upfront and continuing costs for various soil sensors.

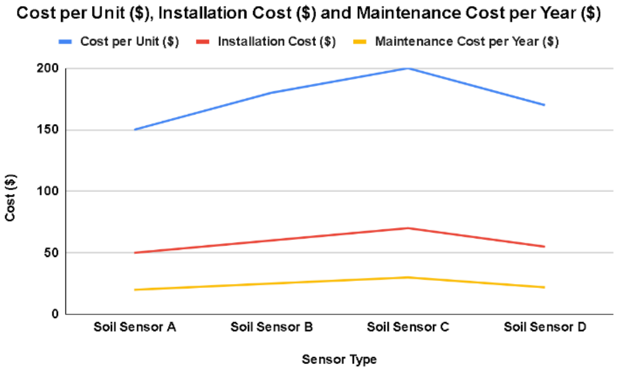

Fig. 6: IoT Sensor Deployment Costs

A combined chart showing the impacts of various fertilizer types—Organic, Chemical, Mixed, and Bio-Fertilizer—on crop yield is shown in Figure 7. The application rate (kg/ha) and yield increase (%) are displayed on the chart using both a bar graph and a line graph, respectively. The application rates of Chemical Fertilizer, at 60 kg/ha, Mixed Fertilizer, at 55 kg/ha, Organic Fertilizer, at 50 kg/ha, and Bio-Fertilizer, at 45 kg/ha, are the greatest, as indicated by the bar graph. The usefulness of chemical fertilizer in raising agricultural productivity is demonstrated by the line graph, which shows that it produces the largest yield increase of 20%. An 18% rise is produced by mixed fertilizer, a 15% increase is produced by organic fertilizer, and a 12% increase is produced by biofertilizer.

This combination graphic gives a thorough understanding of how each type of fertilizer affects crop production by demonstrating the trade-offs between the amount of fertilizer applied and the subsequent yield increase. Knowing which fertilizers provide the optimal balance between application rate and yield improvement is helpful.

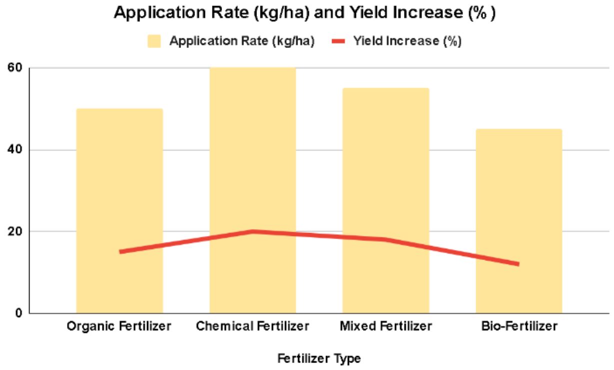

Fig. 7: Impact of Fertilizer Application on Crop Yield

The study used a number of tables and figures to examine different facets of crop and soil management. The average nutrient concentrations in medicinal plants are displayed in Table 1, where nitrogen (N) has the highest concentration and magnesium (Mg) has the lowest, indicating their important roles in enzymatic activities and plant growth. Table 2 and Figure 2 demonstrate that whereas barley exhibits the least gain, maize benefits the most from increased nutrient levels, yielding a 20% rise. In spite of its modest data transmission rate, Soil Sensor A offers better accuracy and longer battery life when compared to other soil sensors, as shown in Table 3 and Figure 3. The requirement for seasonal nutrient management is highlighted by seasonal differences in nutrient levels (Figure 4), with springtime having the highest levels of potassium and nitrogen. Model performance is assessed in Tables 4 and 5, where the Deep Learning Model performs best in classification tasks, as evidenced by its greatest accuracy and F1 Score. Table 5 evaluates the different types of soil and shows that loamy soil has the highest average yield and the least variability. In Figure 6, the costs of soil sensors are compared, with Soil Sensor C being the most expensive. Last but not least, Figure 7 shows how different forms of fertiliser affect production. Chemical fertiliser produces the most increase in yield, highlighting the need of good nutrient management for raising crop productivity.

With the use of extensive data displayed in tables and figures, the study thoroughly examined a number of crop and soil management-related issues. It looked studied the amounts of nutrients in medicinal plants, emphasizing how important nitrogen and magnesium are to plant growth. According to the data, barley gains the least from higher nutritional levels, while maize benefits the most, increasing production by 20%. Despite its modest data transmission rate, Soil Sensor A was found to be the most dependable choice for soil monitoring due to its improved accuracy and longer battery life. The study delves into the seasonal fluctuations in nutrient levels and highlights the necessity of customized approaches to nutrient management, especially in the spring when potassium and nitrogen concentrations are peaking.

Additionally, the research assessed various crop recommendation algorithms; the results showed that the Deep Learning Model performed the best in classification tests. In a comparison of soil types, loamy soil was shown to be the most consistent and productive, but the yield of sandy and clay soils varied more. Even though Soil Sensor C is the most expensive, a cost analysis of soil sensors showed that it might have more sophisticated features. A study was conducted to evaluate the effects of different fertilizers on crop output. The results indicated that chemical fertilizers had the greatest yield increase, highlighting the significance of strategic nutrient management in maximizing agricultural productivity.

V. CONCLUSION

A revolutionary method for maximizing agricultural productivity and sustainability is provided by precision agriculture's integration of IoT-enabled soil sensors, machine learning algorithms, and deep learning models. IoT sensors continuously measure important soil characteristics including electrical conductivity, moisture content, and nutrient levels. This allows them to deliver real-time data that improves crop management, fertilization, and irrigation decisions. By forecasting ideal nutrient levels, categorizing soil types, and suggesting crops that are best suited to the existing soil conditions, the application of machine learning and deep learning algorithms further refines these processes. This allencompassing strategy makes sure that resources are used effectively, minimizing waste and negative environmental effects while increasing agricultural productivity.

The results of the study show how important nitrogen management is for increasing crop yields. The study emphasizes the significance of balanced fertilization tactics by examining soil nutrient levels and their effects on different crop varieties. The findings show that major increases in output can be achieved by adjusting nutrient levels, especially those of nitrogen, phosphorus, and potassium. Furthermore, the need for customized recommendations based on particular crop requirements is highlighted by the variations in nutrient uptake amongst different crops. Improved crop growth and sustainable farming practices are facilitated by more accurate fertilizer management made possible by data-driven insights from IoT sensors and sophisticated algorithms.

All things considered, precision agriculture's use of IoT and machine learning technology marks a substantial breakthrough in contemporary farming. Real-time monitoring, analysis, and optimization of crop and soil conditions results in better-informed and efficient agricultural methods. Farmers are thereby able to attain increased yields, improved resource efficiency, and increased sustainability. This study opens the door for a more intelligent and resilient agricultural future by adding to the expanding body of knowledge about how emerging technologies might be used to address the problems of environmental sustainability and global food security.

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