IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

IoT-Enabled Smart Fertilizer Recommendation System Using Machine Learning

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Abstract:

The proposed work designed a real-time smart fertilizer recommendation system for soil conditions using the Internet of Things (IoT). The proposed system is divided into two modules. The IoT module of the proposed system continuously monitors soil characteristics such as temperature, moisture, and nutrient levels using NPK sensor. The artificial intelligence (AI) module containing artificial neural networks (ANN) analyses the soil characteristics received through NPK and suggests suitable fertilizers. The ANN model achieves a train accuracy of 95%. The proposed system aims to reduce soil degradation, pollution, and economic losses for farmers while increasing crop yield. The system uses affordable IoT hardware with a mobile application for user interface. The AI module is integrated into mobile applications using TensorFlow Lite (TFLite). The proposed system promotes AI-driven smart agriculture solutions and improves sustainability. In the future, the system can be implemented for various crop types.

Keywords: Internet of Things, Artificial Neural Networks, Soil Nutrient Analysis, Smart Soil Fertilization.

1 Introduction

Agriculture is a crucial sector for developing a country [1]. In India, the agriculture sector employs half of the labour force. Food grain production has been increasing yearly, making India one of the producers of crops such as wheat, rice, pulses, sugarcane, and cotton. The two key issues in decreasing agricultural productivity are inadequate irrigation and imbalanced use of soil nutrients; lack of proper soil nutrients results in loss of soil fertility [2]. Better understanding and management of soil nutrients is crucial for refined agricultural practices and improving sustainable land use [3]. Sustainable agriculture requires effective soil health and fertility management. Integrated nutrient management (INM) and integrated soil fertility management (ISFM) are important concepts for profitable agricultural practices. INM manages nutrient stocks for sustained crop production. ISFM focuses on important soil characteristics such as organic matter, structure, and moisture [4].

The Internet of Things (IoT) and Artificial Intelligence (AI) are the key technologies that induce automation across several sectors. IoT is the network of interconnected physical devices that exchange data over the internet [5]. Advancements in IoT see various sensors contributing to the real-time analysis of soil characteristics in smart agriculture. Sensors can be installed on agricultural lands and collect the data consistently. The history of soil data over the years for varying climates is crucial for assessing the farmland nature and fertilizer recommendation.

The primary focus of AI is to provide machines with reasoning, decision-making, learning, and problem-solving capabilities. With proper training, the machines can mimic human intelligence [6]. Various works have utilized AI techniques in smart agriculture to enhance farming practices [7] [8] [9]. The AI models, such as machine learning and deep learning models, can be trained with the soil data and used for automated fertilizer recommendation.

The major challenge in the agricultural field is optimizing fertilizer usage while improving crop yield. Excessive usage of fertilizers leads to water pollution, soil degradation, and increased farm expenses. Insufficient fertilization leads to a decrease in crop yields. Traditional fertilization methods only take static recommendations regardless of real-time soil conditions. IoT and AI in smart agriculture provide data-driven solutions to sustainable farming.

The existing fertilizer recommendation systems depend on a manual soil test and rule-based approaches. Farmers need intelligence to suggest optimal fertilizer type and quantity that considers soil parameters like moisture, temperature, and nutrient level. The proposed work provides a real-time optimized, sustainable fertilizer recommendation system integrating IoT and AI. The contributions of the proposed work are summarized below:

1. The proposed work has developed a real-time soil data collection system. The system was developed using IoT. It measures temperature, humidity, moisture, nitrogen, phosphorus, and potassium levels from the soil. The system gathers the nutrient data from the farmlands and stores them in the cloud storage for future analyses and soil assessments.
2. We have developed an innovative AI method for smart fertilizer recommendation using artificial neural networks (ANN). The proposed model predicts and recommends suitable fertilizer.
3. We have developed a mobile application to provide easy and remote access to the proposed fertilizer recommendation system. The farmers consider it an effective way to access the system as the mobile application provides a user-friendly graphical user interface (GUI) to the farmers.

2 Related Works

Many studies have explored the use of the Internet of Things, Machine Learning, and Artificial Intelligence to improve agricultural practices. This section highlights the relevant research categories under Smart Farming, Crop Yield Prediction, Recommendation Systems of Fertilizer, and AI-powered Agricultural Decision-Making.

Integrating IoT and Machine Learning has revolutionized smart farming by enabling real-time monitoring, automated decision-making, and predictive-based analytics. Sundaresan et al. (2023) developed an IoT-based smart farming framework that leverages Machine Learning by analyzing soil and environmental conditions to enhance crop yield [10]. Khan et al. (2022) proposed a context-aware fertilizer recommendation system utilizing ML and IoT that analyses the requirements of crop and nutrient levels available in the soil to optimize fertilization [11]. Ather et al. (2022) worked on optimal manure composition using AI techniques to ensure improved soil fertility and efficient nutrient absorption [12].

Ikram et al. (2022) explored IoT precision farming solutions to design a smart decision system to maximize crop yield. They utilized sensor data for dynamic decision-making in real time [13]. Perera et al. (2024) introduced EcoGrowAdviser, tailored explicitly to Sri Lankan agricultural practices. They developed an organic fertilizer recommendation system and promoted sustainable farming [14]. Machine Learning models have been used to develop intelligent fertilizer recommendation systems. Gao et al. (2023) proposed a fertilization decision model based on swarm intelligence search algorithms for maize, soybean, and rice to optimize fertilizer application [15]. Indira et al. (2023) designed an AI-powered agricultural monitoring system that integrates IoT sensors to provide real-time fertilizer recommendations and assess soil fertility [16].

Hossain et al. (2023) introduced Smart-Agri, the framework combining ML, IoT, and blockchain for efficient and secure agricultural management, significantly in supply chain optimization and fertilizer planning [17]. Prabavathi et al. (2022) provided a comprehensive review of the Machine Learning approach for predicting essential soil nutrient levels; it highlights AI in optimizing the uses of fertilizer [18]. Dawn et al. (2023) reviewed the recent advancements in AI, ML, and IoT applications in agriculture and their impact on improving crop production efficiently [19]. Rao et al. (2022) developed a machine-learning crop prediction model, enabling farmers to adjust cultivation strategies and anticipate yield variations accordingly [20].

Muhammad et al. (2022) proposed an IoT and cloud-based smart agriculture framework. Integrating ML models for crop yield forecasting meets food security challenges globally [21]. Gupta et al. introduced a machine learning-based feature selection framework, an accuracy of crop yield predictions that improves by identifying critical parameters in agriculture [22]. Raghuvanshi et al. (2022) designed an intrusion detection system in smart irrigation using IoT and Machine Learning algorithms in precision farming [23]. Kuradusenge et al. (2024) introduced SMART-CYPS, an AI-powered crop yield prediction system that leverages IoT and ML through advanced analytics to ensure food security [24]. Bhuiyan et al. (2023) explored predictive analytics in plant biotechnology, utilizing data science methodologies to improve crop productivity and modern agriculture in the significance of AI [25].

Taking the key motivations from these research works, the proposed work designed a real-time soil monitoring and smart fertilizer recommendation system. The proposed work integrates IoT and AI for smart irrigation, soil nutrient analysis, and fertilizer recommendation.

3 Methodology

The proposed work developed an innovative methodology for real-time soil analysis using the Internet of Things. An ANN machine learning model is trained for a fertilizer recommendation system based on the soil characteristics. A mobile application has been developed to provide farmers with an easily accessible user interface. The framework of the proposed work is shown in Figure 1.

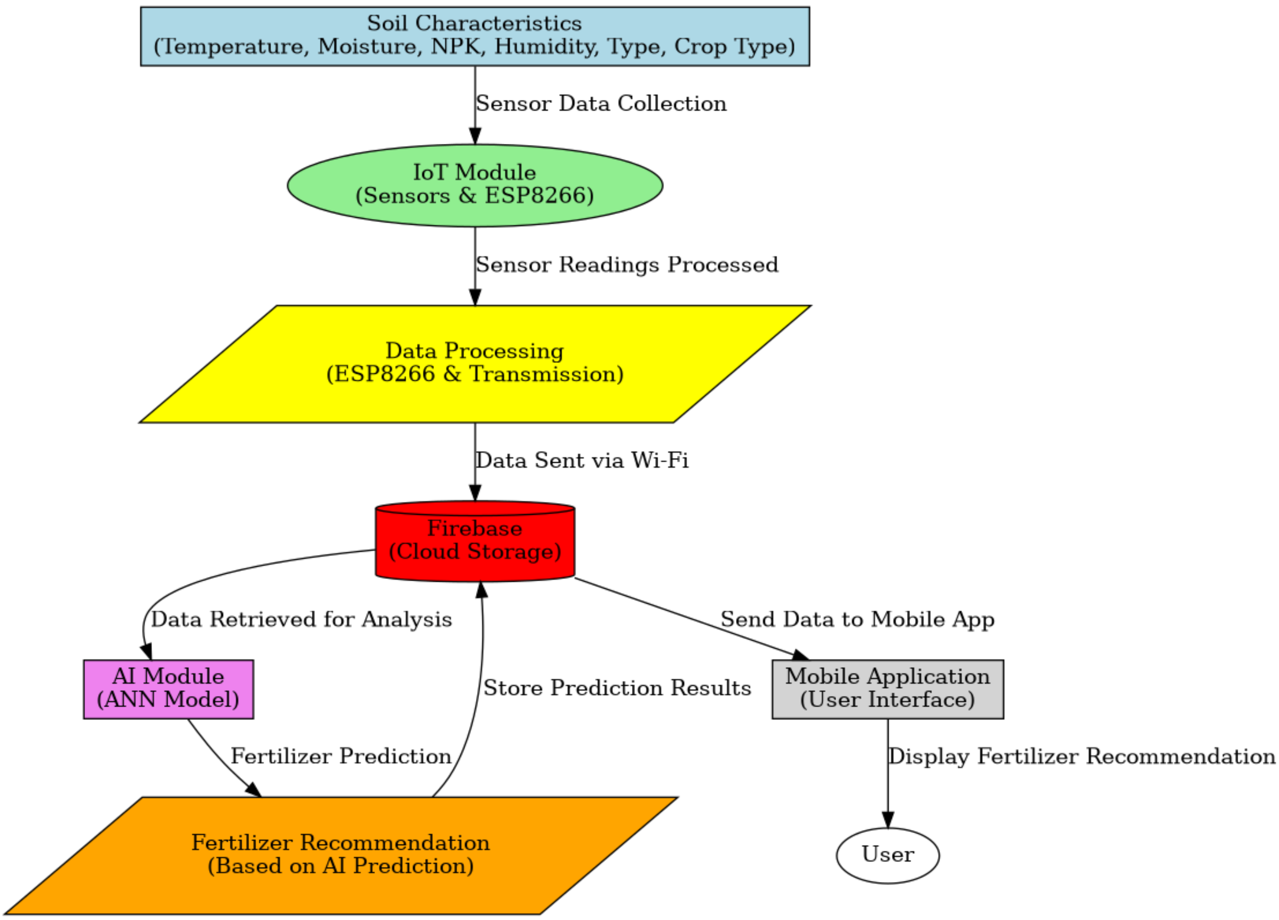


Fig 1. Methodology Framework

3.1 Soil Characteristics Analysis:

Soil properties are known to influence the well-being of farmland and agriculture productivity directly. The crucial indicators for soil evaluation are: Humidity, Temperature, Nutrient Content, Soil Moisture, Soil Kind, and Crop variety. Temperature plays a crucial role in accessing the soil nutrient contents and microbial activities. The soil temperature tracking allows irrigation plans to be adjusted for crops and climate conditions. It helps the plant roots to take nutrients effectively.

The soil moisture level should be monitored consistently to ensure the soil contains enough water for nutrient transportation to support plant growth. The FC-28 soil moisture sensor is used to assess the moisture level. Measuring the nutrient level in soil such as Nitrogen (N), Phosphorus (P), and Potassium (K) is vital for healthy crop cultivation. Nitrogen promotes leaf growth, phosphorus supports flower and root formation, while potassium improves disease resistance. The JXBS-3001 NPK sensor is utilized to measure these nutrient levels and ensure appropriate fertilizers are applied to enhance soil productivity.

Soil humidity is the level of moisture present in the soil, influencing microbial activity and plant transpiration. DHT11 sensor is used to measure the humidity level, ensuring that it is suitable for optimal crop growth with the help of soil conditions. However, excessive humidity can lead to fungal infections, while insufficient humidity affects yield quality.

Soil type influences nutrient holding capacity, aeration, and retention. Different soil types support plant growth with varying abilities. Sandy soils quickly drain, but lack nutrient retention, whereas clayey soils, which hold most nutrients, but cause drainage issues. A balanced mixture of silt, sand, and clay, loamy soil is ideal for more crops. Identifying the type of soil helps to select appropriate fertilizers to improve the structure of soil, fertility, and select the best cultivation.

Crop type plays a significant role as different plants have varying demands of nutrients, determining soil requirements. Some crops do not need much nitrogen-based fertilizers, as they naturally fix nitrogen in the soil. Corn and wheat require high nutrients for optimal yield. By applying customized fertilizers to match specific needs of crops, farmers can adopt precision agriculture techniques, considering the crop type in soil analysis.

3.2. IoT Module:

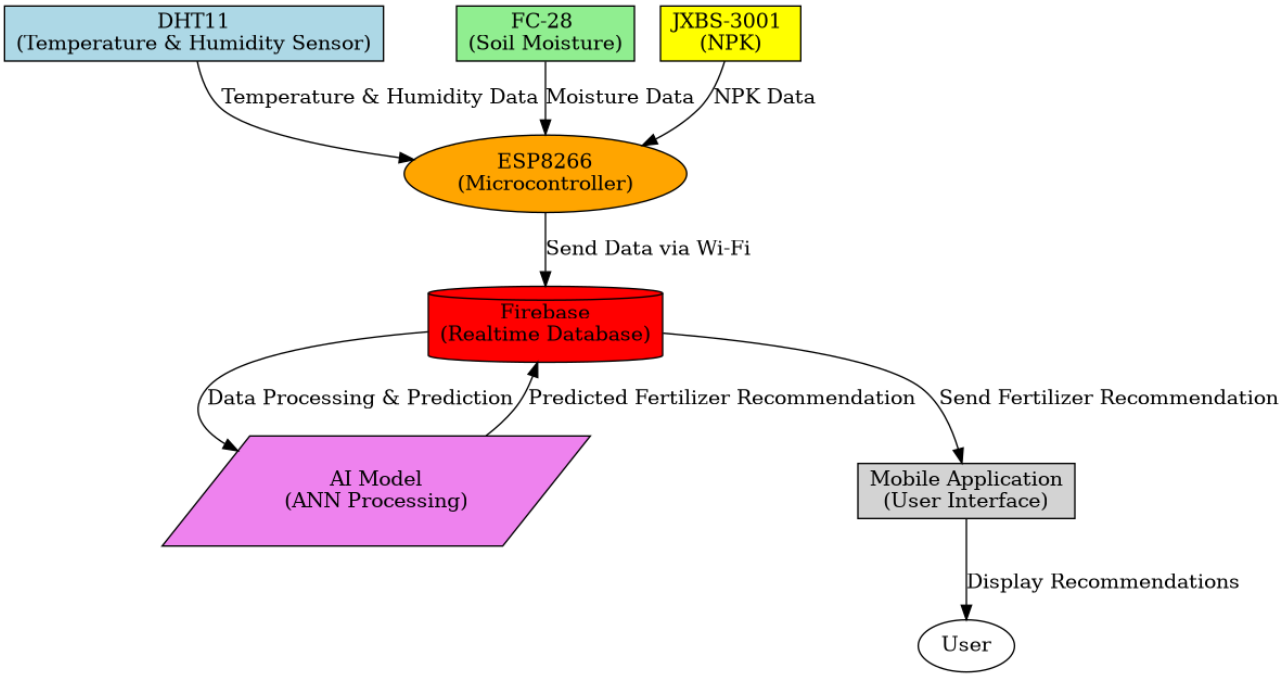


Fig 2. IoT Data Flow Diagram

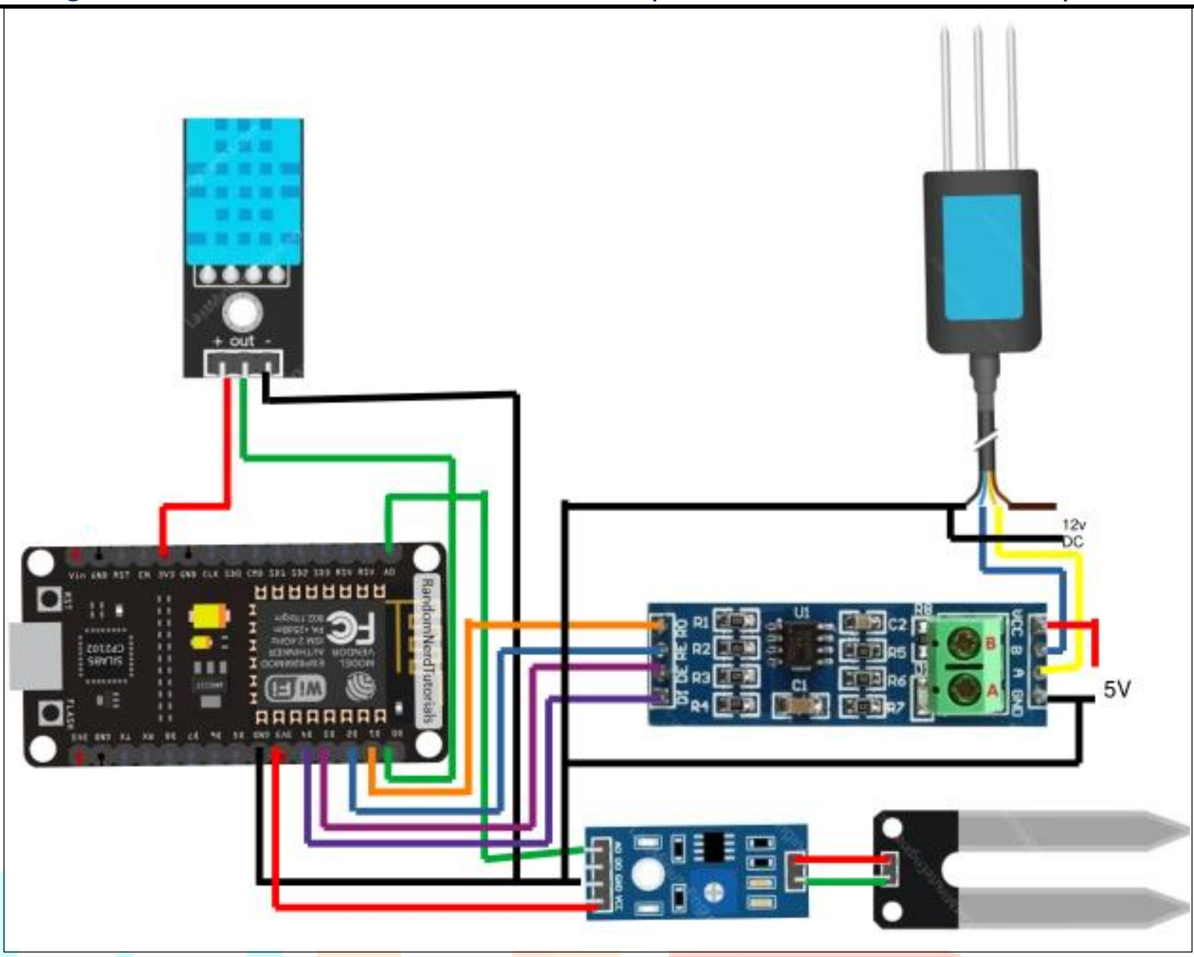


Fig 3: Circuit Diagram

The IoT module plays a significant role in soil data collection. A microcontroller integrated with multiple sensors for monitoring the environment in real-time. The system gathers critical soil parameters such as humidity, temperature, moisture levels, and nutrient composition with the help of DHT11 sensor, NPK sensor with RS485 module, and soil moisture sensor. Continuous data collection ensures work precision that is essential for making agricultural decisions. The microcontroller ESP8266 acts as the central processing unit that collects and processes data from connected sensors and prepares it for transmission. The collected data are periodically updated and stored in a cloud-based database, and farmers can access information through a mobile application in real time. The data flow diagram and circuit design are shown in Figures 2 and 3.

The proposed IoT module prevents overwatering or underwatering by alerting farmers of the water levels in the soil using a soil moisture sensor. It ensures plants receive adequate hydration through proper soil moisture management. The NPK sensor, connected through an RS485 module, calculates the amount of nitrogen (N), phosphorus (P), and potassium (K). Their deficiency can lead to poor yield and plant growth. The RS485 module ensures the accurate data communication between the microcontroller and the sensor. With this module, farmers can select the type of fertilizer and avoid overuse of the chemical promoting sustainable farming. The ESP8266 ensures smooth communication between these sensors for consolidating data and synchronization for precise data logging.

The soil data are collected from the sensors and processed by ESP8266. The data are transmitted over a Wi-Fi module to Firebase Real-time Database. The ESP8266 establishes a stable Wi-Fi connection to send soil parameter updates to the cloud in real-time. The farmers can access soil condition data remotely on their mobile devices. The proposed IoT Module monitors soil conditions in real-time, improves collaboration in farm management.

3.3 AI Module:

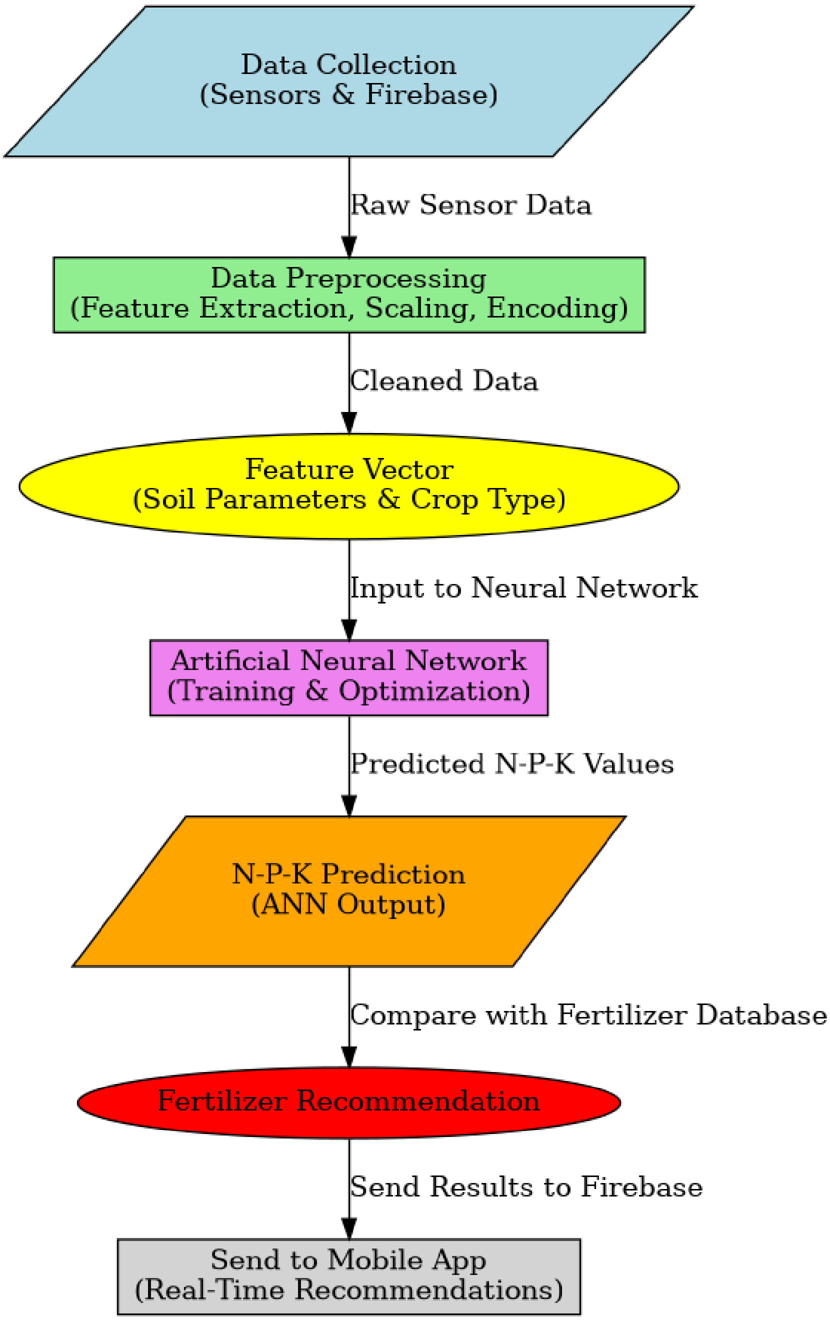


Fig 4: AI Module Workflow

The AI module significantly generates accurate fertilizer recommendations by utilizing collected sensor data based on soil characteristics. The AI module uses artificial neural networks (ANNs) to predict the best fertilizer for soil types and crop varieties. The AI model trained on a structured dataset containing the historical crop and soil data, enables recognizing patterns and making predictions. The model is optimized for edge AI processing and allows inference even in offline mode, in real-time. The AI module identifies nutrient deficiencies, and significantly recommends the optimal fertilization strategies. It improves precision agriculture, and reduces excessive usage of chemicals while increasing the crop yield.

3.4 Preprocessing

The AI model's precision depends on the comprehensiveness and quality of the dataset. In the proposed work, the dataset contains agriculture historical data comprising various attributes such as soil temperature, moisture level, humidity, nitrogen (N), phosphorus (P), potassium (K) concentrates, crop type, and soil type. These features determine the best fertilizer applied to crops and define the soil health. Preprocessing steps are carried out to enhance the quality of the dataset. Imputation techniques are used to handle missing values, incomplete data entries. The missing/incomplete data are replaced with mean or mode values, nor inferred from similar data points. For better compatibility, the categorical data such as soil and crop type are converted into numerical representations using One-Hot Encoding. The features are standardized to ensure that all numerical values within a comparable range. Standardization (Z-score normalization) scales the features and improves the model performance. The dataset is split into training, validation, and test sets.

The standardization technique can be mathematically represented as shown in Eq 1.

$$X' = \frac{X-\mu}{\sigma} \tag{1}$$

Where,

X' and X are the normalized and original feature values, while μ and σ represent mean and standard deviation of the features.

3.5 FEATURE VECTOR

A feature vector is a structured input to train the AI model. In the proposed fertilizer recommendation system, the feature vector consists of environmental and multiple soil parameters: humidity, temperature, soil moisture level, nitrogen (N), phosphorus (P), potassium (K), crop type and soil type. The proposed work applies feature selection to select important features for the model. Recursive Feature Elimination (RFE) is utilized to eliminate irrelevant and redundant features. It helps the model focus on high impact data and enhance the prediction accuracy. Principal Component Analysis (PCA) identifies the significant variables contributing to fertilizer recommendations. RFE. Mathematically, the feature vector can be represented as Eq 2.

$$X=[\, x^1 , x^2 , x^3 , \dots , x^n \,] \tag{2}$$

where x^i represents each feature value such as humidity, temperature, soil moisture level, and NPK level.

A description of the features are given in Table 1.

Table 1. Features description

Feature Name	Description	Data Type	Unit
Soil Temperature	The temperature of the soil affects nutrient availability	Continuous	°C (Celsius)
Soil Moisture	Water content in the soil, essential for crop growth	Continuous	Percentage (%)
Soil Humidity	Humidity level in the soil influences microbial activity	Continuous	Percentage (%)
Nitrogen (N)	Essential nutrient for plant growth and leaf development	Continuous	mg/kg
Phosphorus (P)	Affects root development and flowering in plants	Continuous	mg/kg
Potassium (K)	Improves plant disease resistance and water retention	Continuous	mg/kg
Soil Type	Categorization of soil based on texture and composition	Categorical	Clay, Sandy, Loamy, etc.
Crop Type	Type of crop cultivated influences fertilizer needs	Categorical	Wheat, Rice, Maize, etc.

3.6 The Proposed ANN Architecture

The Artificial Neural Network (ANN) analyses the soil characteristics and predicts the suitable fertilizer. The ANN model contain multiple layers: input layer, hidden layers, and output layer. The input layer receives the feature vector, which represents the collected soil data from the IoT sensor in real-time. Each hidden layer consists of artificial nodes, which process the input using weighted connections, activation functions (ReLU), and bias terms. The architecture of the proposed ANN is shown in Figure 5. The mathematical representation of the ANN working is given in Eq. 3.

$$z_j = \sum_{i=1}^{n} w_{ij}\, x_i + b_j \tag{3}$$

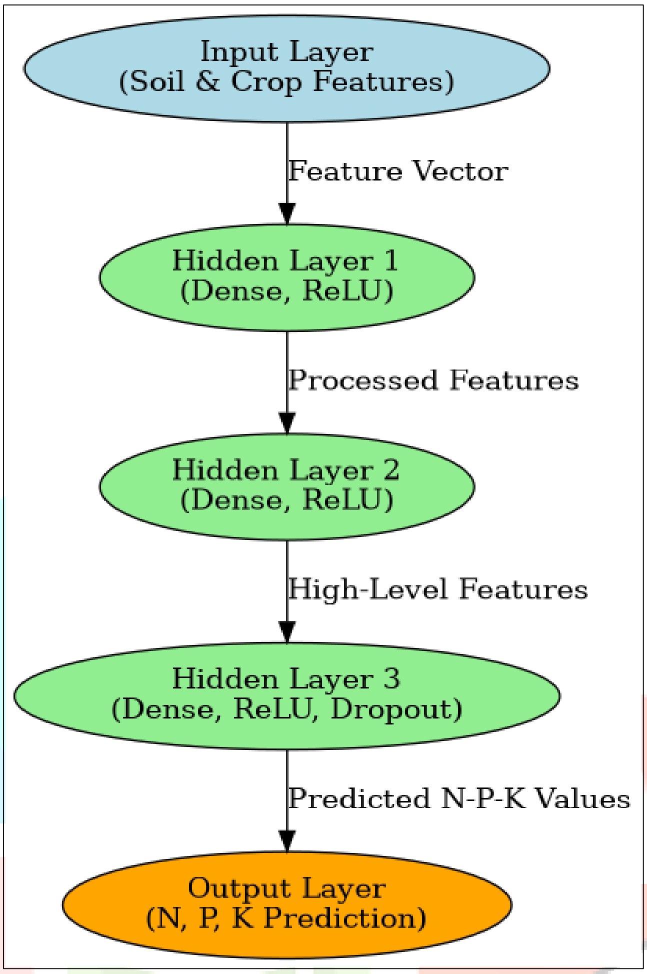
$$a_j = f(z_j) \tag{4}$$

Where,

x_i represents input features, w_{ij} are the weights associated with each connection, b_j and f(z) are the bias term and activation function.

Based on the learnings from the input features, the output layer generates the final prediction. The proposed model analyzes the soil characteristics and predicts the suitable fertilizer for the crop field.

Fig 5. ANN Architecture



3.7 MOBILE APPLICATION

The mobile application serves as the interface connecting the farmer and the intelligent fertilizer suggestion system. The application is created using Android (Java) and Firebase, and enables users to access real-time soil data, receive fertilizer recommendations, and monitor environmental conditions from any location. The integration of the Firebase Real-time Database to the application ensures that sensor information collected from IoT devices is swiftly stored, processed, and accessed. It provides quick insights into soil conditions and agricultural requirements. The application includes an intuitive graphical user interface (GUI), allowing farmers to interact with the system easily. The main screen shows humidity, temperature, soil moisture level, and nutrient levels (NPK), soil type, crop type, enabling users to quickly evaluate soil conditions. The backend of the application is designed for data access and modifications, ensuring that farmers obtain precise recommendations. Additionally, Firebase offers user authentication, ensuring safe logins and customized dashboards. It helps farmers to monitor historical data and analyze seasonal patterns.

The mobile application is designed with a feature notification system that alerts the farmers about critical soil conditions. When the soil moisture level drops below an optimal threshold, the system app sends an instant alert recommending irrigation. When NPK concentrations are unbalanced, the application notifies the farmer to apply the required fertilizer. The mobile application transforms traditional farming practices into a smart and data-driven approach by integrating IoT, AI, and cloud computing. The mobile application bridges the gap between agriculture and technology. The proposed system helps ensure optimal crop health and prevent soil degradation.

4 Results & Discussion:

Experimental Setup

The proposed work is divided into two modules. The IoT module was implemented in real time with DHT11, FC-28, and JXBS-3001 sensors. ESP8266 node MCU board along with RS485 module is used for controlling the sensors. The entire IoT module and its programming are done using Arduino IDE. The AI module was implemented using Jupyter Notebook in Google Colab. The Python 3 Google engine was used to train and test the model performance.

Dataset

The proposed work used the fertilizer prediction dataset from the Kaggle repository [26]. The dataset contains 100 samples with nine columns, where 8 represent input features, and 1 represents the label.

Experimental Results

The performance of the proposed neural network model using accuracy, precision, recall, F1 - Score, ROC - AUC Score, Log Loss, Matthews Correlation Coefficient (MCC), Cohen's Kappa, and balanced accuracy.

The training accuracy and loss are plotted in Figure 6. From the figure, the model attained an accuracy of 95.00 %, it indicates the correct recommendations of fertilizer in high level.

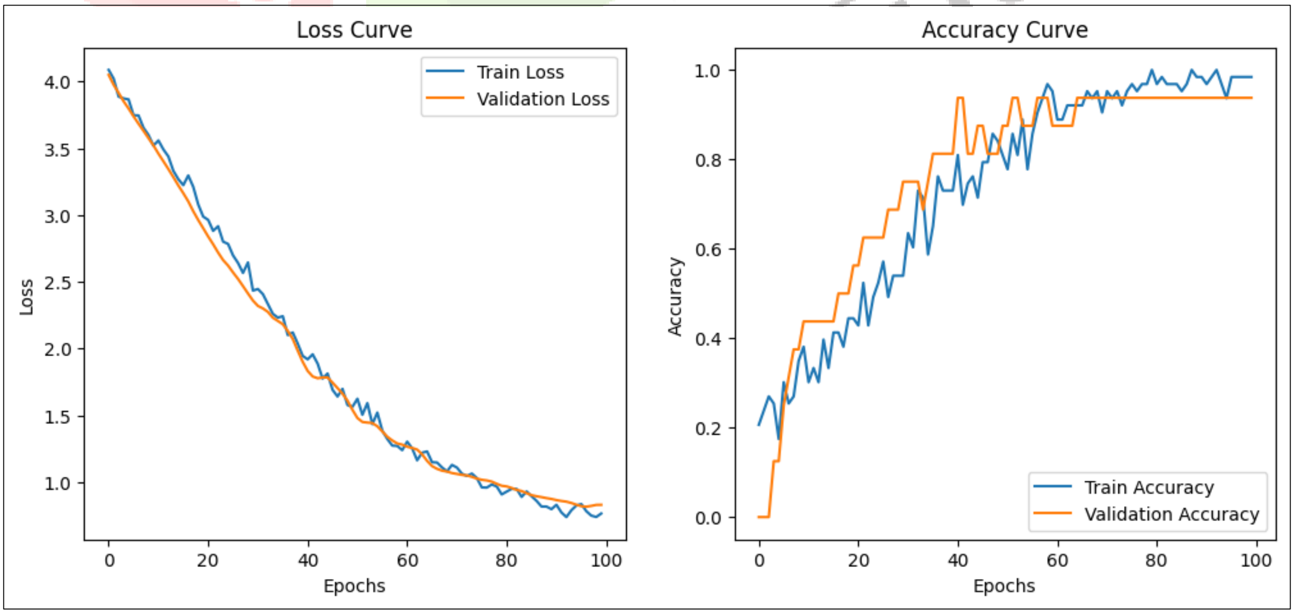


Fig 6: Neural Network model accuracy and loss

The evaluation results of the proposed model are given in Table 2. From the table, the precision and recall demonstrate ability of model to make reliable and consistent predictions while minimizing false positives and false negatives. The formulas to calculate precision and recall are given in Eq (5) and (6).

$$Precision = \frac{TruePositives}{TruePositives+FalsePositives} \quad (5)$$

$$Recall = \frac{TruePositives}{TruePositives+FalseNegatives} \quad (6)$$

Moreover, F1-Score which consider the both of precision and recall, and it confirms the balanced performance of the model. The formula for F1 score is given in eq (7)

$$F1 = 2\ x\ \frac{Precision\ x\ Recall}{Precision+Recall} \quad (7)$$

Table 2. Evaluation Results

Metric	**Neural Network**
Acccuracy	0.900
Precision	0.875
Recall	0.900
F1-Score	0.8771
Matthews Corrcoef	0.8835
Cohen's Kappa	0.8780
Balanced Accuracy	0.8095

The Log Loss of the model is depicted in figure 7. It highlights model uncertainty in classification, which, relatively low, suggest further optimization.

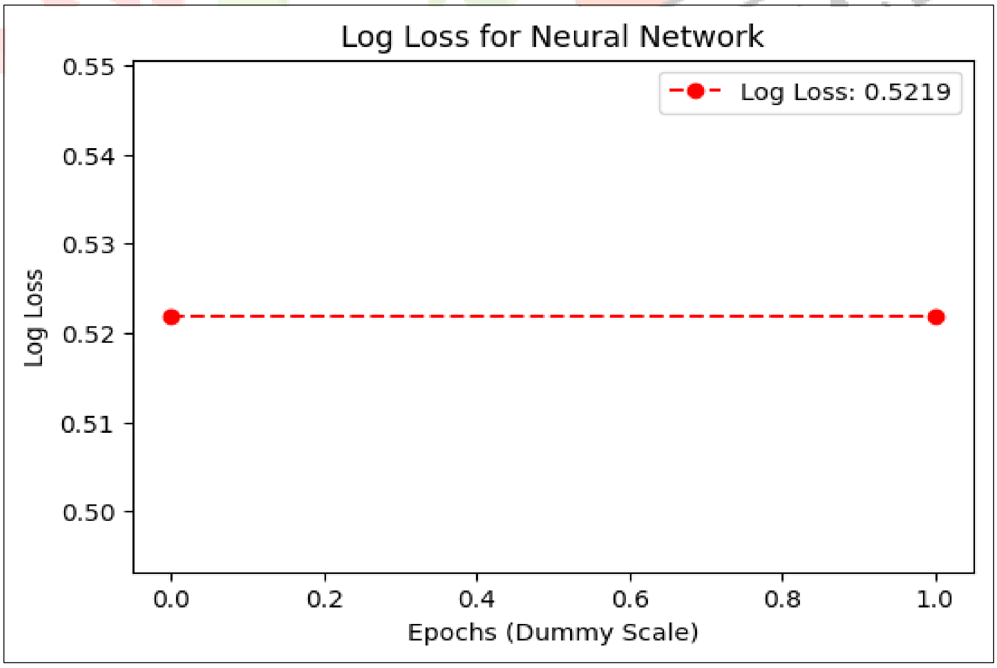


Fig 7: Log Loss for Neural Network

The Matthews Correlation Coefficient and Cohen's Kappa indicate high level of relation between the predicted and actual labels, validate the robustness of model. The MCC and Cohen's kappa values are plotted in figure 8.

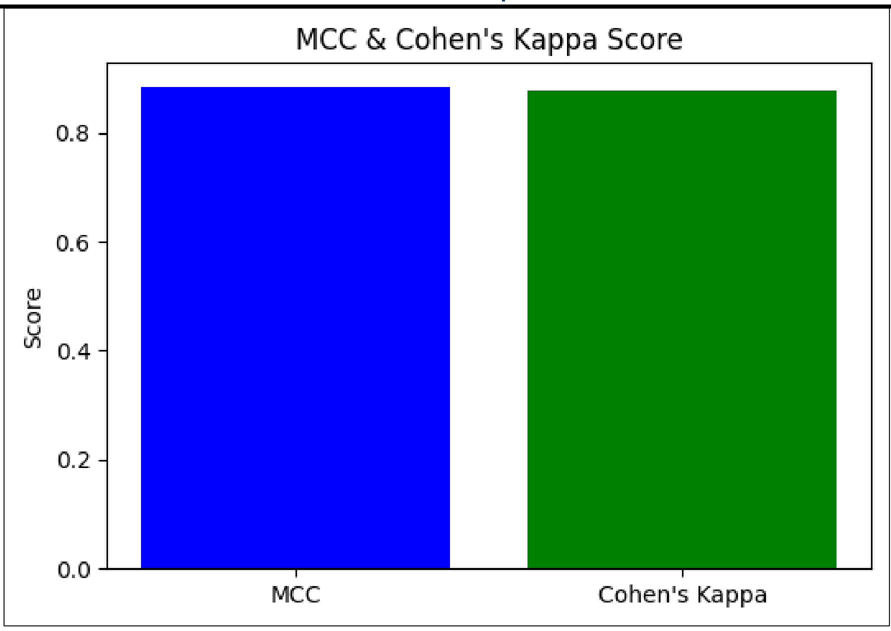


Fig 8: MCC & Cohen's Kappa

Balanced Accuracy ensure the model across all fertilizer classes maintain the fair performance, even in case of data distribution in imbalanced. The calculation for balanced accuracy is shown in Eq. (8).

$$Balanced\ Accuracy = \frac{Sensitivity + Specificity}{2} \tag{8}$$

The feature importance analysis, as illustrated in Figure 9 below, highlights most influential features in the recommendation system of fertilizer. Soil Nutrient Levels (N, P, K) are the most critical factors and align with agronomic knowledge to plant growth and development, these nutrients are fundamental. Moisture and Humidity levels also influence the fertilizer recommendations significantly. Temperature has a moderate impact in determining fertilizer based on climatic conditions. Soil Type and Crop Type have relatively low importance score, implying that while contribute to predictions.

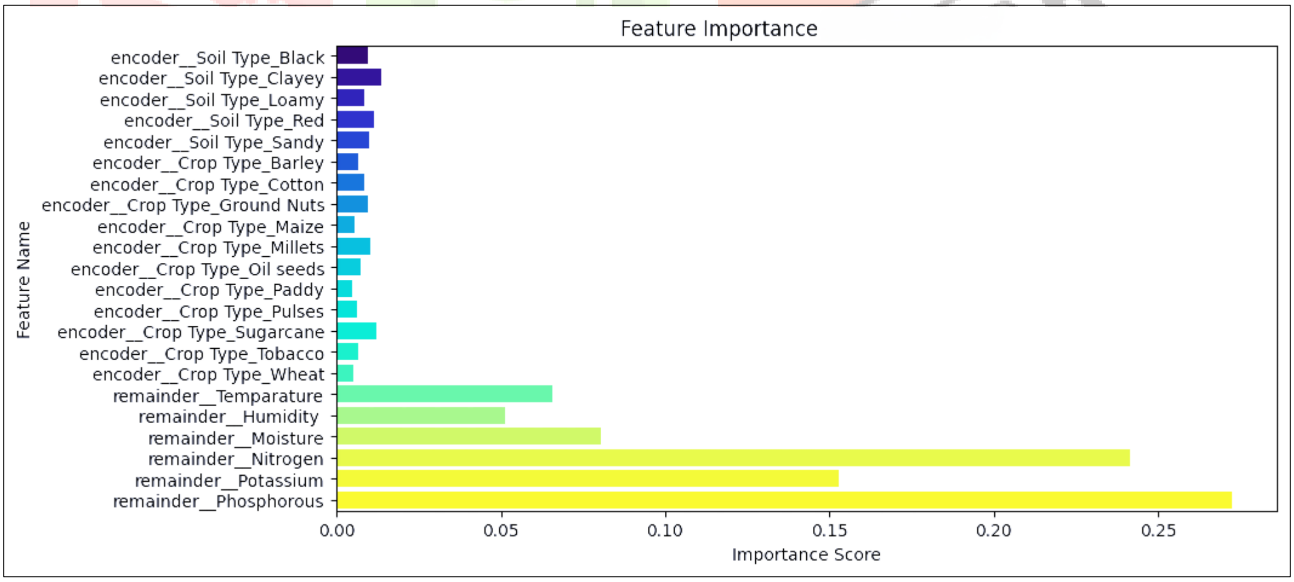


Fig 9: Feature Importance Analysis

The mobile application's GUI is shown in Figure 10. The proposed IoT module identified the soil nutrient levels accurately when applied in farmlands. The evaluation results of the model shows fair performance of the proposed system in fertilizer recommendation. To improve the evaluation scores, the model need to be trained with more samples. In the future, the model can be trained with the increased number of real-time samples for various soil types and crop types.

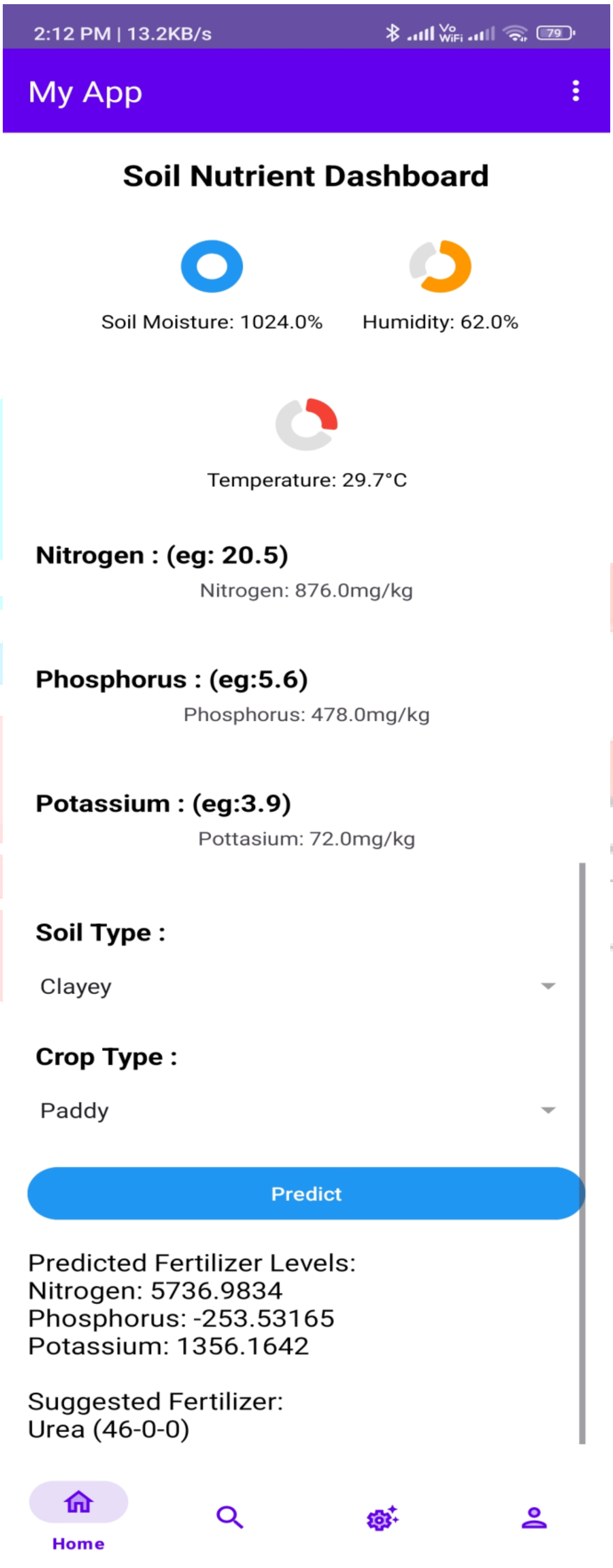


Fig 10: Mobile Application

5 Conclusion

The proposed work integrates innovative and intellectual technologies such as IoT, AI, and cloud computing for a smart agriculture fertilizer recommendation system. The soil quality in the crop field is consistently monitored using an IoT system. An intelligent AI system is prepared with an ANN model to predict the nutrient levels in the soil. The proposed recommendation system uses a mobile application with a convenient graphical user interface. The proposed model has achieved an accuracy score of 95%. In the future, the accuracy can be improved with advanced model architectures and preprocessing. The proposed work can be extended to a variety of soils and farmlands in the future in smart agriculture.

Acknowledgements

We express our sincere gratitude to Electronics Club, The Gandhigram Rural Institute for their generous financial support, which has been instrumental in the successful completion of this research. Their support has provided the necessary resources and opportunities to this work.

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