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IoT-based AI-integrated device for farmers: A recommendation system for crop cultivation

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***Abstract*—Agriculture serves as the primary source of livelihood for the majority of the population. However, crop yields in the country often remain low due to various factors, including prolonged cultivation of the same crops, insufficient knowledge regarding fertilizer types and quantities, and susceptibility to crop diseases in Bangladesh. Previously, several studies were conducted, but the equipment used in the research was too cost-ineffective. To address these challenges, a comprehensive system leveraging advanced technology and data analytics methodologies was developed to assist Bangladeshi farmers. This system utilizes sensors to collect data on moisture levels and soil quality, which are then analyzed to recommend suitable crops and necessary fertilizers for specific fields. Additionally, the system includes a module for detecting potato leaf diseases, aiding farmers in identifying and treating this common ailment. Moreover, the system is capable of calculating the required amount of fertilizer for the field. A thorough evaluation involving farmers was conducted to assess the system's effectiveness, revealing that it performs efficiently in providing recommendations for crop selection, fertilizer application, and plant disease detection.**

***Index Terms*—precision agriculture, soil quality, crop yield, potato leaf disease, IoT, ML, AI**

I. Introduction

The focal domain of this system is agriculture, a critical sector in the economy of Bangladesh. Agriculture accounts for a substantial portion of Bangladesh's GDP (15.89%) and labor force (45.1%). With approximately 16.5 million farming families, agriculture sustains a significant portion of the country's population. Nearly half of Bangladesh's populace is engaged in agriculture, utilizing over 70% of the land for crop cultivation [1].

In remote regions of Bangladesh, numerous farmers lack access to information on modern agricultural techniques, technologies, and resources. This dearth of knowledge leads to suboptimal crop yields, exacerbated by the repetitive cultivation of the same crops, which diminishes soil fertility over time. Furthermore, farmers struggle with fertilizer selection and plant disease identification, resulting in disappointing harvests.

Previous research has explored solutions such as sensor-based data collection and machine learning for soil analysis, yet these approaches often suffer from high costs, usability issues, and language barriers. Additionally, there's a noticeable gap in utilizing image processing for plant disease detection in Bangladesh.

To address these challenges, this paper proposes an IoT-enabled machine learning system designed to deliver accurate and timely agricultural guidance to Bangladeshi farmers. Utilizing NPK and capacitive soil moisture sensors, the system gathers data on soil nutrients and moisture, which are then analyzed using machine learning algorithms to recommend suitable crops and fertilizers. Furthermore, the system employs image processing to detect potato plant diseases and determine fertilizer requirements. Accessible through a Bengali-language Android app built with Flutter, this system aims to provide farmers with easy-to-understand recommendations.

This research contributes a cost-effective and practical solution to enhance agricultural productivity in Bangladesh. The primary objectives include developing an IoT-based machine learning system for crop and fertilizer recommendation and plant disease detection, utilizing sensors to collect soil data, employing machine learning algorithms for data processing, simplifying farming technology usage, increasing production and economic growth, reducing time and costs associated with soil analysis, and detecting anomalies in soil and plants. Upon successful completion, the outcome was the development of a combination of IoT and AI-based recommendation systems for farmers regarding crop cultivation, which gave promising results.

II. Literature Review

Over the years, numerous studies have highlighted the significant advancements in IoT [2] and machine learning applications in various fields [3], [4] specially agriculture [10], [11]. While some of these studies have demonstrated remarkable success, others have raised questions regarding feasibility and user experience.

Kanimozhi et al. [5] proposed a system that uses sensors, such as the DHT11 sensor, to observe and measure temperature and humidity levels in the field. These sensors provide real-time data on environmental variables that are critical for crop growth. Platforms like Thingspeak send the data collected from sensors to the cloud for storage and analysis. This enables data management to be centralised and easy to access. But there are more factors that need to be considered, as proposed by Kumar R et al. [6]. This research collected data on multiple factors that affect crop production, such as location, weather, soil type, soil composition, and harvesting techniques. Including the values of nitrogen, phosphorus, and potassium, which are the core nutrients of soil, allows for proper crop and fertilizer recommendations. S. Gupta et al. [7] proposed such a method where the application uses a dataset containing variables such as nitrogen, phosphorus, potassium levels in the soil, temperature, humidity, pH value, and rainfall in order to predict the suitable kind of crop for cultivation. Nitrogen, phosphorus, and potassium values are used for fertilizer recommendations. The application also integrates a plant disease detection system that utilizes image analysis of leaves to accurately identify illnesses that impact crops. Most likely, the system uses computer vision techniques to analyze and categorize images for disease detection. The same research was done by S.A.Z.

Rahman et al. [11], where the data were pH and organic matters like nitrogen. These attributes represent the soil classes. After feeding data into the model, it predicts suitable crops. Bhadani et al. [13] presented a system utilizing an Arduino Uno microcontroller, an FC28 hygrometer, and DHT11 sensors to measure soil moisture, temperature, and humidity, respectively. But it only gives values from the sensors; no model is used for predicting crops. The comparison analysis with other papers is shown in Table I

TABLE I
COMPARATIVE ANALYSIS

Ref	Objectives	Model	Accuracy
1	To enhance agricultural productivity by utilizing IoT technologies, sensors, and data analytics.	N/A	N/A
2	To propose crop selection method to maximize the net yield rate of the crop over the season	ANN, SVM, Boosting	N/A
3	To provide crop recommendations, recommend suitable fertilizers based on nitrogen, phosphorus, and potassium levels, and identify plant diseases by analyzing leaf images.	SVM, K_Means, EfficientNet	Crops:92% Disease: N/A
4	To create a precise model capable of precisely forecasting soil series by analyzing chemical properties and geographical attributes.	SVM,KNN, Bagged-trees	92.93%
5	To provide farmers with advanced agricultural methods to precisely monitor essential elements of crop growth.	N/A	N/A

III. CONCEPTUAL DESIGN OF THE SYSTEM

A. Architecture of the system

The system architecture is depicted in Figure 1. It comprises two main components: hardware and software. The hardware component encompasses sensors and a microcontroller. Soil nutrient levels are measured by the sensors and transmitted to the microcontroller. Subsequently, the values are relayed from the microcontroller to Firebase and then to the Android app.

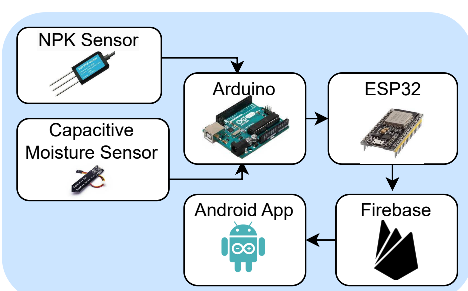


Fig. 1. System Architecture

B. IOT and ML model architecture

The system's IoT and ML architectures are illustrated in Figures 2 and 3, respectively. In the IoT architecture, Nitrogen, Phosphorus, Potassium, and Humidity values are transmitted to Firebase through Arduino and ESP32. Subsequently, the data is relayed from Firebase to the mobile app for processing and displaying results. In the ML architecture, the process begins with data collection, followed by storage and pre-processing to prepare it for model fitting. Next, the data undergoes training within the models, followed by evaluation.

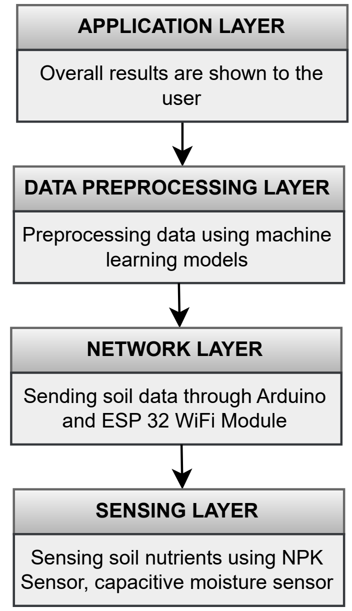


Fig. 2. IOT Architecture

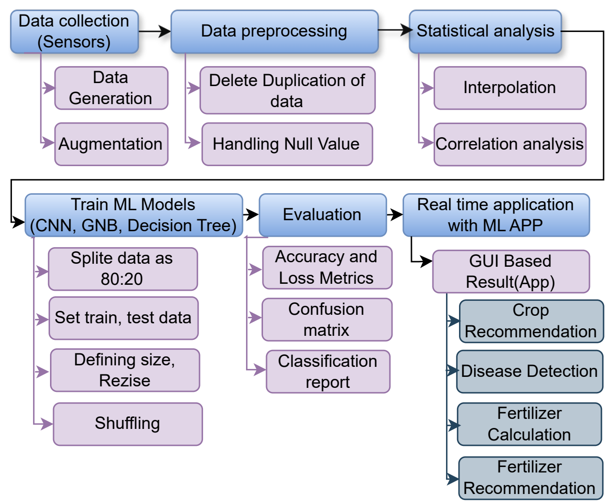


Fig. 3. ML Architecture

C. Dataset Description

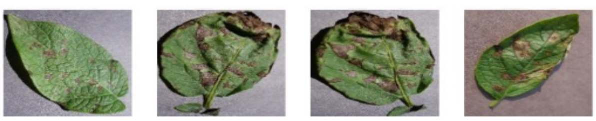
In the Crop Recommendation module, the dataset comprises nitrogen, phosphorus, and potassium values along with their corresponding Bangladeshi crops. In the Fertilizer Recommendation module, the dataset includes nitrogen, phosphorus, and potassium values, along with crop names and their corresponding fertilizer names. Meanwhile, in the Disease Detection module, the dataset comprises potato images categorized into three classes: Early Blight, Healthy, and Late Blight. *Alternaria solani*, a fungus, is responsible for early blight in potatoes. This disease can also affect tomatoes, other plants in the potato family, and certain types of mustard. The spots initially appear as tiny, black, dried fragments, which later expand into brown-black, circular-to-oval regions. The areas are frequently surrounded by veins, giving them an angular appearance. The late blight of potatoes is a severe condition caused by the pathogen *Phytophthora infestans*. It has an impact on potatoes, tomatoes, and sometimes eggplants and other plants belonging to the potato family. Leaf spots begin as small, pale to dusky green, asymmetrical dots. The dots are often surrounded by pale green to yellow bands. The regions lack vein borders, but they have the ability to expand over them [15]. Refer to Figure 4 for sample representations of these datasets.

	N	P	K	humidity	label
0	90	42.0	43.0	82.002744	rice
1	85	58.0	41.0	80.319644	rice
2	60	55.0	44.0	82.320763	rice
3	74	35.0	40.0	80.158363	rice
4	78	42.0	42.0	81.604873	rice

Crop

Nitrogen	Potassium	Phosphorous	Moisture	Crop Type	Fertilizer Name
37	0	0	38	Maize	Urea
12	0	36	45	Sugarcane	DAP
7	9	30	62	Cotton	14-35-14
22	0	20	34	Tobacco	28-28
35	0	0	46	Paddy	Urea

Fertilizer



Disease

Fig. 4. Sample of Datasets

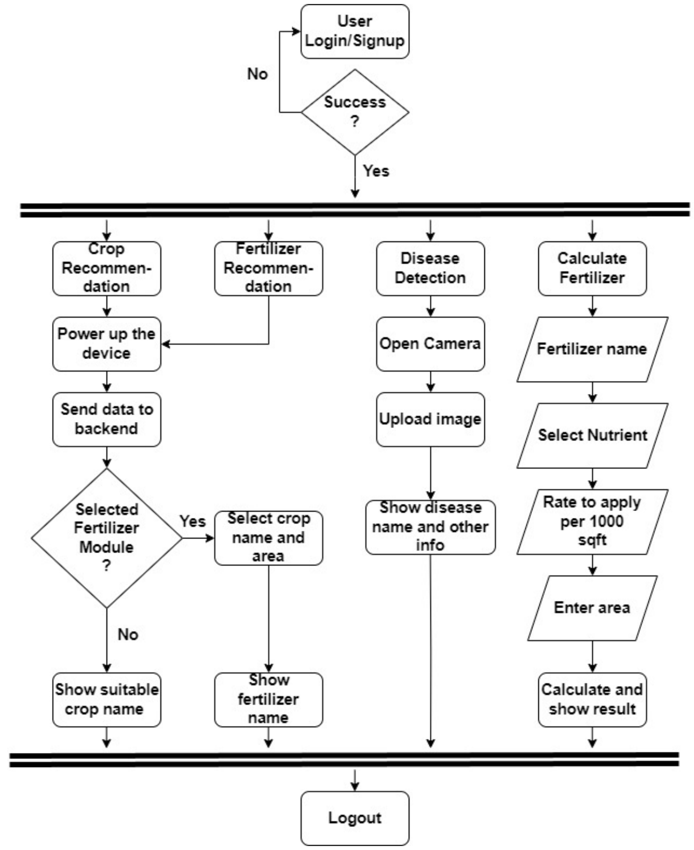


Fig. 5. Workflow Diagram

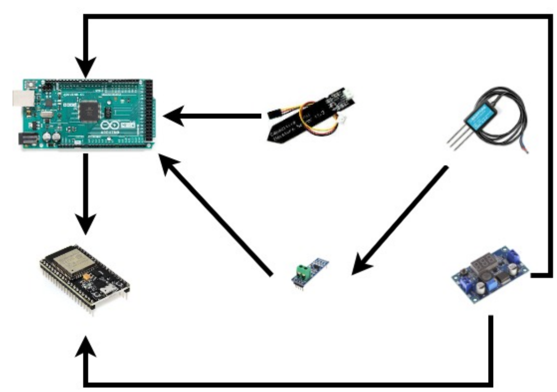


Fig. 6. Communication Between Components

D. Workflow Diagram

The workflow diagram and the algorithm of the system is depicted in Figure 5 and Algorithm 1. Initially, the user will access and either register or log in to the system. Upon successful authentication, the user can proceed to select one of the four modules available (e.g., Crop Recommendation, Fertilizer Recommendation, Disease Detection). In the case of crop and fertilizer recommendations, the system will retrieve data from sensors, initiating the processing routine. However, for fertilizer recommendations, the user is prompted to provide additional input, specifically the crop name. For disease detection, the user is required to upload an image, triggering the image processing algorithm.

To calculate fertilizer requirements, the following inputs are necessary:

- Name of the fertilizer.
- Nutrients.
- Rate to apply per 1000 sqft.
- Area to apply.

Then after processing, it will show the results about fertilizer, nitrogen, phosphorus, potassium amount.

IV. Prototype Design and Development

The whole system can be divided into two parts:

A. Hardware Module Design

The primary function of the hardware involves retrieving soil values through the utilization of the following components:

NPK Sensor: Also referred to as the Nitrogen, Phosphorus, Potassium Sensor, this portable and cost-effective sensor provides swift response times and offers reasonably accurate measurements. It facilitates real-time monitoring of soil nutrient concentrations, contributing to smart agriculture practices. NPK sensor has three electrodes. These three electrodes generate electrical signals proportional to the concentration of the specific ion present. Users can easily operate NPK sensors by simply inserting a probe into the soil. But sometimes it may require calibration to improve accuracy.

RS485 Modbus Module: Direct interfacing of the NPK sensor with Arduino is not feasible. Therefore, an RS-485 transceiver module is necessary to convert UART serial streams into RS-485 for

Algorithm 1: Algorithm for the whole procedure

```
Initialisation ;
if Login/Signup then
    if Crop Recommendation then
        Power up the device ;
        Send data to backend ;
        Output: Show Suitable crop name
    end
    if Fertilizer Recommendation then
        Power up the device ;
        Send data to backend ;
        Select crop name and area ;
        Output: Show fertilizer name
    end
    if Disease Detection then
        Open Camera ;
        Upload Image ;
        Output: Show disease name and other info
    end
    if Calculate Fertilizer then
        Input  : Fertilizer name
        Input  : Select nutrient
        Input  : Rate to apply per 1000 sqft
        Input  : Enter area
        Output: Calculate and show result
    end
else
    Try again ;
end
```

communication with Arduino. Modbus, an open-source and royalty-free industrial communication protocol, serves as the standard for data exchange. The Modbus TCP protocol enables data transmission across Ethernet TCP/IP networks, as well as RS-485, RS-422, and RS-232 interfaces.

Capacitive Soil Moisture Sensor: Unlike traditional resistive sensors, this capacitive soil moisture sensor employs capacitive sensing to gauge soil moisture levels. Its corrosion-resistant construction materials ensure longevity, while an internal voltage regulator allows operation within the voltage range of 3.3 to 5.5 volts. This module is compatible with both 3.3V and 5V low-voltage MCUs.

Additionally, the hardware setup includes microcontrollers such as Arduino and ESP32, along with a Step-down Transformer to complement the functionality of the system. After connecting all components with the breadboard, and 12v battery with the help of jumper wires, the final circuits are given in Figure 7 and 8:

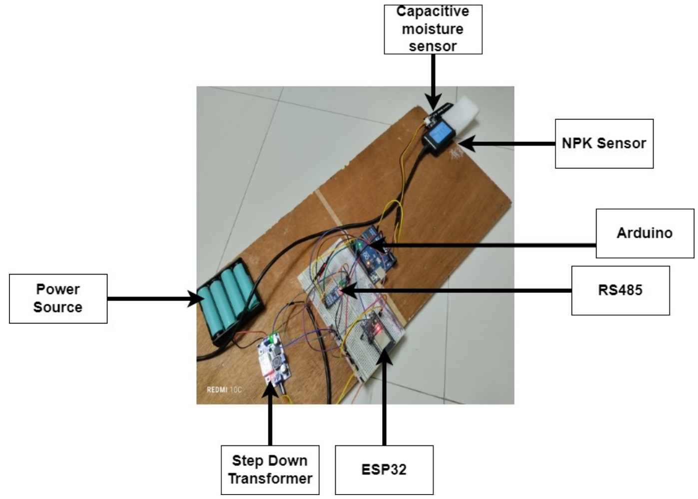


Fig. 7. Main Circuit

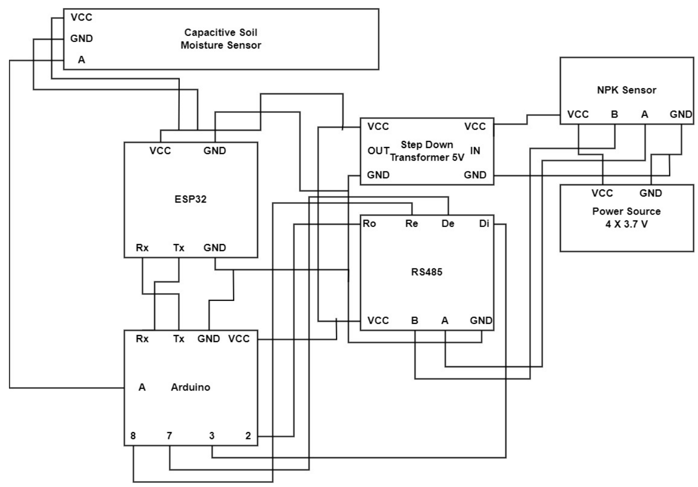


Fig. 8. Circuit Diagram

B. Software Module Design

The Software part of the system consists of the following sections:

1) Frontend: To ensure farmers can easily navigate the system, a Bengali-language Android app was developed using Flutter for the frontend. Flutter, an open-source UI software development kit (SDK) developed by Google, empowers developers to craft high-performance and visually appealing applications for various platforms using a single codebase. While Flutter can be utilized for creating desktop and web applications, it excels in crafting mobile apps for both iOS and Android platforms. Within the app, users can effortlessly select from three modules to perform operations and review past soil data.

2) Backend: To transmit data collected by hardware to the mobile application and maintain a record of past data as historical records, the real-time database of Google Firebase was utilized. With Firebase's NoSQL cloud-hosted database, developers can seamlessly store and synchronize data across multiple clients in real time. This database provides features such as real-time synchronization, offline data accessibility, and automatic conflict resolution, all while utilizing a JSON data format.

3) ML Algorithms: Three Machine learning algorithms were used for implementation of three modules. Their details are given in Table II

TABLE II
MODULE AND RESPECTIVE ALGORITHMS

Module	Algorithm
Crop Recommendation	GNB Classifier
Fertilizer Recommendation	Decision Tree
Disease Detection	CNN

A popular and straightforward probabilistic machine learning approach for classification tasks is the Gaussian Naive Bayes (GNB) classifier. It leverages the principles of Bayes' theorem and assumes independence among the features of each class. In both classification and regression scenarios, decision trees are widely embraced as a machine learning technique. Represented as a tree-like structure, with internal nodes denoting features, branches representing decision rules, and leaf nodes depicting outcomes or predictions, decision trees are intuitive and effective. Convolutional Neural Networks (CNNs) constitute a class of deep learning algorithms frequently applied in tasks involving grid-like data, such as image and video recognition, computer vision, and related applications. CNNs excel at automatically learning hierarchical features from raw input data, capturing both low-level and high-level representations. Their shared weights in convolutional layers, along with local receptive fields, enable proficient handling of translation-invariant patterns. For implementing these algorithms, Jupyter Notebook serves as an ideal platform, offering an interactive computing environment supporting various programming languages like Python, R, and Julia. Widely used in data science, education, research, and data analysis, Jupyter Notebook is highly versatile.

To interface the application with the ML models, Flask API is employed. This adaptable Python web framework simplifies the development of web applications and APIs, facilitating seamless integration with machine learning models.

4) Connection Between hardware and software: To facilitate crop and fertilizer recommendations, data will be transmitted from the hardware to Firebase. Subsequently, the Android app will retrieve this data from Firebase and automatically populate the corresponding fields. The only exception is with fertilizer recommendations, where the crop name needs to be manually entered.

No hardware is necessary for disease detection and fertilizer calculation since these processes involve image processing, uploading, and manual inputs.

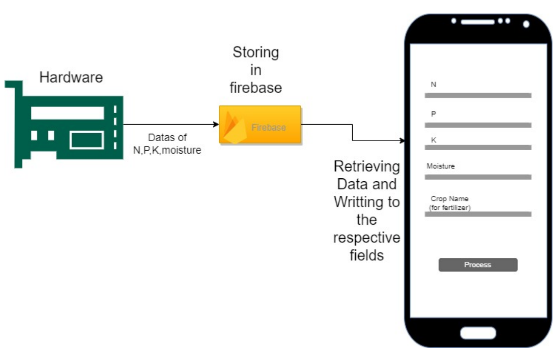


Fig. 9. Hardware software connection for crop and fertilizer recommendation

V. Evaluation of the System

Five farmers participated in testing the mobile application, each engaging with it for 4 to 5 minutes. The assessment sought to gauge the application's usability, comprehensiveness, and gather insights for future enhancements. Before the evaluation, the farmers received a briefing on the mobile application, including its features, characteristics, and the objectives of the assessment. They willingly agreed to test the application and offer feedback for improvements. Throughout the evaluation, each farmer interacted with the application for a minimum of 4 to 5 minutes. The evaluation report is shown in Table III. The GUI results are shown in Figure 10. The model parameters and performance are shown in Table IV and V

VI. Results and Discussions

The system employs NPK and humidity sensors, utilizing machine learning algorithms to detect optimal crops and fertilizers, as well as to diagnose potato plant diseases. Moreover, it can estimate the required fertilizer quantity in the field. However, a primary limitation arises: the system lacks waterproofing, rendering it susceptible to malfunction during rainfall. Additionally, occasional sensor malfunctions occur due to heightened sensitivity. Nevertheless, future endeavors aim to automate the entire system (e.g., via robotics) and enhance its usability by waterproofing it. We have plans to extend our research to automated disease detection (Like [14]) and soil condition analysis recommend Pesticide fertilizer.

TABLE III
Evaluation Table

Task	Module	Results	No of Attempts (M±SD)	Task Completion Time (M±SD)	No of times asking for help (M±SD)
T1: Verify Login	SW	100%	1±0.54	1.3±0.44	0.6±0.54
T2: Verify Crop Recommendation	HW & SW	96%	1±0	3±0	0±0
T3: Verify Fertilizer Recommendation	HW & SW	94%	1±0	3±0	0±0
T4: Verify Disease Detection	SW	100%	1±0	2±0	0.4±0.54
T5: Verify Calculation of Fertilizer	SW	100%	1±0	1.2±0.44	0±0

TABLE IV
Model Parameters

Model	Layers	Output Shape	Parameter
CNN	sequential (Sequential)	(32, 256, 256, 3)	0
	conv2d_12 (Conv2D)	(32, 254, 254, 32)	896
	max_pooling2d_12 (MaxPooling2D)	(32, 127, 127, 32)	0
	conv2d_13 (Conv2D)	(32, 125, 125, 64)	18,496
	max_pooling2d_13 (MaxPooling2D)	(32, 62, 62, 64)	0
	conv2d_14 (Conv2D)	(32, 60, 60, 64)	36,928
	max_pooling2d_14 (MaxPooling2D)	(32, 30, 30, 64)	0
	conv2d_15 (Conv2D)	(32, 28, 28, 64)	36,928
	max_pooling2d_15 (MaxPooling2D)	(32, 14, 14, 64)	0
	conv2d_16 (Conv2D)	(32, 12, 12, 64)	36,928
	max_pooling2d_16 (MaxPooling2D)	(32, 6, 6, 64)	0
	conv2d_17 (Conv2D)	(32, 4, 4, 64)	36,928
	max_pooling2d_17 (MaxPooling2D)	(32, 2, 2, 64)	0
	flatten_2 (Flatten)	(32, 256)	0
	dense_4 (Dense)	(32, 64)	16,448
	dense_5 (Dense)	(32, 3)	195
GNB Classifier	None	None	None
Decision Tree	None	None	None

A. Novelty and implication of the research

The article suggests that by utilizing IoT and AI, farmers can access advanced recommendations for crop cultivation, potentially revolutionizing agricultural practices with data-driven insights.
Novelty: The integration of IoT and AI tailored for agriculture is a novel approach, offering a sophisticated recommendation system to optimize resource usage and enhance crop yields.

VII. Conclusion

The proposed development of an IoT-based AI-integrated device for farmers has yielded promising outcomes, offering recommendations for crop selection, fertilizer application, and plant disease detection. This system enables farmers to easily navigate and choose among three modules for operations while accessing historical soil data. Furthermore, it utilizes machine learning models and Flask

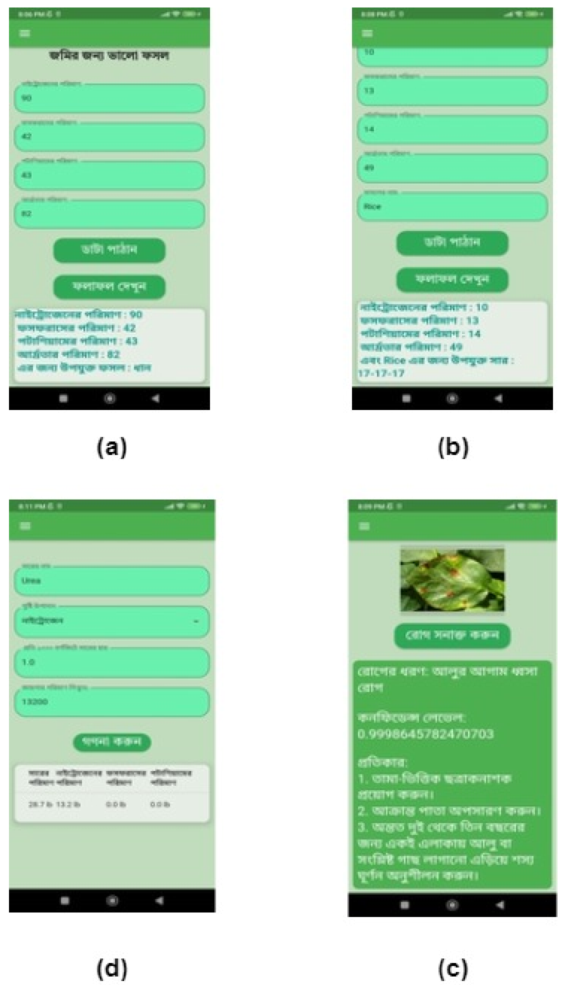


Fig. 10. GUI of the results: (a) Crop Recommendation, (b) Fertilizer Recommendation, (c) Disease Detection, (d) Fertilizer Calculation

TABLE V
PERFORMANCE TABLE

Model Name	Used For	Accuracy
GNBClassifier	Crop Recommendation	94%
Decision tree	Fertilizer Recommendation	90%
CNN	Disease Detection	96%

API to seamlessly connect the application with the ML algorithms. The significance of the research lies in its potential to revolutionize agriculture by offering farmers a cutting-edge recommendation system powered by IoT and AI. This system enables real-time insights, optimizing resource usage, improving yields, and promoting sustainable farming practices.

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Declaration: The authors declare that the use of ChatGPT or any LLM is not applicable in the preparation of this research paper.

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