JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

AI BASED FARMING GUIDANCE FOR KARNATAKA REGIONS

An IoT and Machine Learning Based Decision Support System

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Abstract : Farmers in Karnataka must make several interdependent decisions on crop selection, fertilizer application, expected yield and market timing, yet these decisions are often guided by experience rather than by data. This paper presents an AI based farming guidance system that integrates the Internet of Things (IoT), Machine Learning (ML) and a Decision Support System (DSS) in a single mobile application. The system works in two modes. In Sensor Mode, an ESP32 microcontroller collects soil and environmental parameters such as temperature, humidity, soil moisture, pH and NPK (nitrogen, phosphorus and potassium) levels. In Non-Sensor Mode, the farmer provides the location and soil type, and historical agricultural data are used instead. After validation and preprocessing, the ML models recommend three suitable crops in priority order, suggest a fertilizer and predict the crop yield, while an ARIMA time-series model forecasts market demand. The results are presented through a Flutter mobile application supported by Firebase Authentication and Cloud Firestore. A prototype of the application and of the sensor interface has been implemented, and its outputs are reported. The system aims to reduce resource wastage and support informed agricultural decisions; its effectiveness depends on sensor accuracy, dataset quality, model performance and internet connectivity.

IndexTerms - Smart Agriculture, Internet of Things, Machine Learning, Crop Recommendation, Fertilizer Recommendation, Yield Prediction, ARIMA, ESP32, Flutter, Karnataka.

I. INTRODUCTION

Agriculture is one of the most important sectors in Karnataka. It supports the livelihood of a large number of farmers and contributes to the economy of the state. During cultivation, farmers must take several important decisions, such as selecting a suitable crop, applying the right fertilizer, estimating the crop yield and understanding market demand. These decisions are often based on traditional practices, personal experience and limited information. Changes in weather, soil characteristics, nutrient availability and market conditions make them more difficult. Inappropriate crop selection or excessive use of fertilizer affects both productivity and the efficient use of resources. Therefore, there is a need for a system that gives farmers timely and data-based guidance.

The integration of IoT and ML can help to address these challenges. IoT sensors for soil moisture, pH, temperature, humidity and NPK can collect information about the soil and its environment. The data can be transmitted using an ESP32 microcontroller and processed along with historical agricultural datasets. ML techniques can analyze these inputs to identify suitable crops and to recommend fertilizers. They can also estimate the expected crop yield and analyze market data to predict demand. By combining real-time sensor information with historical data, a system can give more useful and systematic farming guidance.

This paper presents “AI Based Farming Guidance for Karnataka Regions”, a decision support system that provides several types of agricultural guidance through a user-friendly mobile application. The system supports both sensor-based and non-sensor-based operation, depending on the availability of sensors. Its major outputs are crop recommendation, fertilizer recommendation, yield prediction and market demand prediction. The main contributions of this work are: (i) an integrated architecture that combines IoT data acquisition, four ML models and a DSS; (ii) a dual-mode design that keeps the system usable when sensors are not available; and (iii) a Flutter mobile application with Firebase integration that presents all recommendations on a single platform.

The rest of this paper is organized as follows. Section II reviews the related literature. Section III identifies the problem and Section IV states the objectives. Section V describes the proposed methodology, Section VI lists the hardware and software requirements, and Section VII presents the implementation results. Section VIII outlines the applications, and Section IX concludes the paper with the future scope.

II. LITERATURE SURVEY

[1] **M. Khan, S. Ali, and F. Rahman, IoT and machine learning-based smart farming system for crop and soil management,** presents an integrated approach combining IoT sensors and machine learning algorithms for monitoring soil parameters and crop conditions. The study highlights real-time data acquisition, automated decision-making, and improved crop productivity through predictive analytics. It demonstrates efficient soil management and irrigation control; however, the system depends heavily on continuous connectivity, lacks detailed cost analysis, and does not fully address scalability and maintenance challenges in diverse agricultural environments.

[2] **L. Zhang, Y. Chen, and H. Liu, Hybrid machine learning approach for crop selection and yield prediction**, proposes a hybrid model combining multiple machine learning techniques to improve accuracy in crop recommendation and yield estimation. The paper highlights enhanced prediction performance, efficient data utilization, and adaptability to different environmental conditions. It provides a robust analytical framework; however, the model complexity is high, requires large datasets for training, and lacks practical field-level validation in real-time agricultural scenarios.

[3] **M. Nawaz and M. I. K. Babar, IoT and AI for smart agriculture in resource-constrained environments: Challenges, opportunities and solutions**, presents the integration of IoT and AI technologies for improving agriculture in low-resource settings. The study highlights the use of low-cost sensors, machine learning models, and cloud platforms for crop monitoring, soil analysis, and yield prediction, while addressing challenges like limited connectivity and energy constraints. It provides a strong conceptual framework; however, it lacks practical implementation and real-time validation, and does not deeply address hardware limitations and large-scale deployment complexity.

[4] **R. K. Singh, P. Verma, and S. Tiwari, AI-based crop recommendation and yield prediction using IoT data,** discusses the use of IoT-generated data combined with AI models for accurate crop selection and yield forecasting. The paper highlights improved decision-making through real-time data analysis and predictive modeling, enhancing productivity and resource optimization. It shows effective integration of AI with IoT; however, it requires high-quality datasets, lacks discussion on data security, and does not fully explore cost and deployment challenges for small-scale farmers.

[5] **A. Kumar and V. Singh, Smart farming using artificial intelligence and IoT**, discusses the application of AI and IoT in enhancing agricultural productivity through automated irrigation, pest detection, and crop health monitoring. The paper emphasizes real-time monitoring systems and data-driven decision-making to optimize resource utilization. It demonstrates the potential of smart farming technologies; however, it provides limited analysis on data security, lacks detailed performance evaluation, and does not sufficiently address scalability and cost constraints.

[6] **Xiaomin Li, Smart agriculture using edge computing and IoT,** explores the use of edge computing with IoT to enable real-time data processing and faster decision-making in agriculture. The study highlights reduced latency, improved responsiveness, and decreased dependence on cloud infrastructure for applications like irrigation control and disease detection. It shows efficiency in time-sensitive operations; however, the system architecture is complex, requires high initial investment, and does not fully address maintenance and energy consumption issues.

[7] **K. Kuwata and T. Shibasaki, Machine learning approaches for crop yield prediction and price forecasting**, presents machine learning techniques for predicting crop yield and market prices. The study highlights the use of historical and environmental data to improve forecasting accuracy and support decision-making for farmers and stakeholders. It provides insights into market trends and agricultural planning; however, it depends on large datasets, may suffer from data inconsistency, and lacks real-time adaptability in rapidly changing conditions.

[8] **S. R. Babu, A. Kumar, P. Reddy, and K. Srinivas, Crop recommendation using artificial neural networks,** discusses the use of ANN models for recommending suitable crops based on soil and environmental parameters. The paper highlights improved prediction accuracy and efficient classification of crop suitability. It demonstrates the effectiveness of neural networks in agriculture; however, it requires extensive training data, may face overfitting issues, and lacks comparison with other advanced machine learning models.

[9] **A. Goap, D. Sharma, A. K. Shukla, and C. R. Krishna, IoT-based smart farming system using machine learning,** presents an IoT-enabled system integrated with machine learning for monitoring crop conditions and automating farming operations. The study highlights real-time sensing, predictive analytics, and efficient resource management. It shows significant

improvement in productivity and system automation; however, it depends on reliable network connectivity, involves high implementation cost, and does not fully address scalability in large farming areas.

[10] **M. Wolfert, L. Ge, C. Verdouw, and M. J. Bogaardt, Big data in smart farming: A review,** provides a comprehensive review of big data applications in agriculture. The paper highlights data-driven decision-making, integration of IoT and analytics, and improved efficiency in farming practices. It offers a broad understanding of smart farming technologies; however, it lacks specific implementation details, faces challenges in data management and privacy, and does not provide concrete solutions for small-scale adoption.

[11**] R. Priyadharshini, S. Kavitha, and M. Rajesh, Fertilizer recommendation system using machine learning,** presents a machine learning-based system to recommend suitable fertilizers based on soil nutrients and crop requirements. The study highlights improved nutrient management, optimized fertilizer usage, and enhanced crop productivity through data-driven decisions. It demonstrates the effectiveness of predictive models in agriculture; however, it depends on accurate soil data, lacks real-time field validation, and does not address cost and usability for small-scale farmers.

[12] **R. Sujatha and P. Isakki, Crop recommendation system using machine learning,** discusses a system that uses machine learning algorithms to suggest suitable crops based on soil and climatic conditions. The paper highlights improved crop selection accuracy, efficient use of agricultural resources, and better yield outcomes.

[13] **Y. Peng, X. Wang, and L. Zhang, Crop yield prediction using satellite imagery and machine learning**, explores the use of satellite data combined with machine learning for predicting crop yield. The study highlights improved accuracy through remote sensing data, large-scale monitoring capabilities, and efficient analysis of environmental factors. It provides a scalable solution for yield estimation; however, it depends on high-quality satellite data, involves complex processing, and may not be accessible for small farmers.

[14] **M. Ikram, S. Ahmed, and A. Hussain, Crop yield prediction using ensemble machine learning models,** presents the use of ensemble techniques to enhance prediction accuracy in crop yield estimation. The paper highlights better performance compared to individual models, improved reliability, and efficient handling of complex datasets. It demonstrates robustness in prediction; however, the model complexity is high, requires significant computational resources, and lacks real-time deployment analysis.

[15] **A. Goap, D. Sharma, A. K. Shukla, and C. R. Krishna, IoT-based smart agriculture monitoring system using sensors and machine learning**, discusses an IoT-enabled system integrated with machine learning for monitoring environmental and crop conditions. The study highlights real-time data collection, automated decision-making, and improved resource management. It shows enhanced productivity and efficiency.

[16] **P. Dubois, J. Martin, and L. Bernard, Soil moisture prediction using machine learning techniques,** presents machine learning models for predicting soil moisture levels to support irrigation planning. The study highlights improved water management, efficient irrigation scheduling, and better crop health. It provides a useful approach for precision agriculture; however, it requires continuous data input, may face accuracy issues with limited data, and lacks real-time implementation details.

[17] **S. S. Patil and R. Patil, Agricultural price forecasting using regression models**, discusses the use of regression techniques to predict crop prices based on historical data. The paper highlights improved market insights, better decision-making for farmers, and efficient planning of crop sales. It demonstrates the usefulness of predictive analytics in agriculture; however, it depends on historical trends, may not adapt well to sudden market changes, and lacks integration with real-time data.

[18] **A. O. Abioye, M. S. Zainal, and N. M. Wahab, IoT-based smart irrigation system for precision agriculture**, presents an IoT-based irrigation system that uses sensors to automate water supply based on soil conditions. The study highlights water conservation, efficient irrigation management, and reduced human intervention. It shows effectiveness in precision agriculture; however, it relies on sensor accuracy, requires initial investment, and does not fully address maintenance and scalability issues.

[19] **J. Ramesh and M. Karthik, Precision agriculture using data mining techniques**, explores the use of data mining methods to analyse agricultural data for improving decision-making. The study highlights pattern recognition, efficient resource utilization, and improved productivity. It demonstrates the role of data analytics in agriculture; however, it requires large

datasets, lacks real-time processing capabilities, and does not address implementation challenges.

[20] **K. Lakshmi, S. Devi, and R. Kumar, IoT-based crop monitoring system**, presents an IoT-based system for monitoring crop and environmental conditions using sensors. The paper highlights real-time monitoring, improved crop management, and efficient use of resources. It shows benefits in automation and data collection however, it depends on network connectivity, involves setup costs, and lacks detailed performance evaluation in large-scale farming environments.

Table 1: Summary of the reviewed literature and its limitations

Focus area	References	Limitations observed
IoT-based monitoring and irrigation	[1], [3], [9], [15], [16], [18], [20]	Sensor reliability and accuracy, maintenance and implementation cost, noisy data, dependence on power and continuous internet connectivity.
Crop and fertilizer recommendation	[2], [4], [5], [8], [11], [12], [19]	Dependence on dataset quality and completeness, limited regional applicability, limited real-time adaptability, model complexity.
Yield prediction	[2], [7], [13], [14]	Need for large and reliable datasets, high cost and limited access to satellite data, complex and computationally heavy ensembles.
Price and market forecasting	[7], [17]	Sudden market changes and unpredictable fluctuations reduce forecasting accuracy.
Edge computing and big data	[6], [10]	Limited processing and storage capacity of edge devices; large storage and processing requirements for big data.

Overall, the literature shows that the performance of existing systems depends on the quality, quantity and accuracy of datasets and sensor readings. Many of them require continuous internet connectivity, a reliable power supply, costly sensors and regular maintenance, which is difficult in rural and small-scale farming. Most approaches also address only one task, such as crop recommendation, irrigation, fertilizer recommendation, yield prediction or price forecasting, and some need high computational resources because of complex ML or ensemble models. There is therefore a need for an integrated and user-friendly system that combines real-time IoT data with ML to provide several agricultural services through a single platform. The proposed work addresses this need by combining crop recommendation, fertilizer recommendation, yield prediction and market demand prediction in one decision support system for Karnataka regions.

III. Problem Identification

The following problems are identified in current farming practice. (i) *Traditional decision-making:* farmers rely on traditional knowledge and experience for crop selection, fertilizer application and planning, which may not reflect the current soil, weather and market conditions. (ii) *Unsuitable crop selection:* variations in soil type, rainfall, temperature and climate across Karnataka make it difficult to select the most suitable crop for a region. (iii) *Improper fertilizer usage:* lack of accurate information on soil nutrients and crop requirements leads to excessive or insufficient fertilizer, which increases cost and affects soil health. (iv) *Lack of real-time monitoring:* continuous information on soil moisture, pH, temperature, humidity and NPK levels is not usually available. (v) *Uncertainty in yield:* accurate estimates of the expected yield are not available before cultivation, which makes it difficult to plan resources, labor, storage and harvesting. (vi) *Uncertainty in market demand and prices:* changes in demand, supply, season and price make it difficult to decide which crops will give better economic returns. (vii) *Lack of an integrated system:* existing solutions often address one aspect, such as weather, irrigation or soil monitoring, whereas farmers need an affordable and simple system that integrates IoT data, crop and yield prediction, fertilizer recommendation and market information in one mobile application.

IV. Objectives

The objectives of this work are: (i) to develop an AI based smart farming system using IoT, ML and cloud technologies that helps farmers make better agricultural decisions; (ii) to collect real-time soil and environmental data (moisture, pH, NPK, temperature and humidity) using sensors and an ESP32; (iii) to recommend suitable crops and fertilizers based on soil and environmental conditions, so that productivity improves and unnecessary fertilizer use is reduced; (iv) to predict the crop yield using ML models, which helps in planning resources, labor and harvesting; (v) to analyze crop market trends from historical data, which helps farmers understand demand and plan cultivation; and (vi) to develop a simple and affordable Flutter mobile application that provides crop, fertilizer, yield and market recommendations on one platform.

V. Proposed Methodology

A. System Architecture

The architecture of the proposed system is shown in Fig. 1. IoT sensors measure the soil and environmental parameters, and the ESP32 module sends the readings over Wi-Fi to the backend system using HTTP or MQTT. The data processing unit validates, cleans and preprocesses the data. The four ML models then generate crop, fertilizer, yield and market demand predictions. The DSS combines the soil, weather, crop, yield and market information to produce suitable recommendations, which are displayed in the mobile application. When sensors are not available, the farm details entered by the farmer and the historical datasets are given to the data processing unit instead of the sensor data.

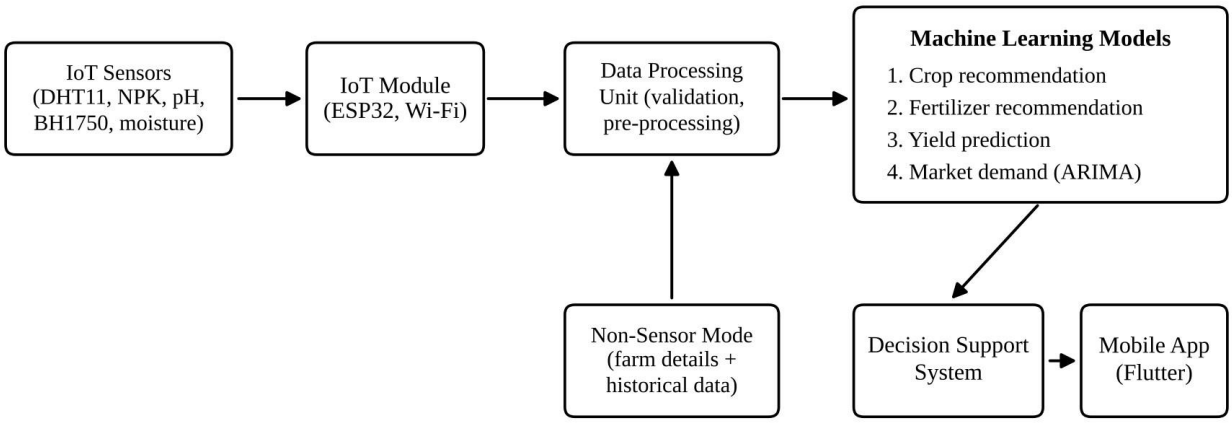

Fig. 1. Block diagram of the proposed AI based farming guidance system

B. Operating Modes

The application asks the farmer whether sensors are installed on the farm (Fig. 3(b)). In *Sensor Mode*, the ESP32 collects temperature, humidity, soil moisture, pH and NPK data, and these real-time readings are used for the analysis. In *Non-Sensor Mode*, the farmer enters the farm details, namely the farmer name, region and soil type (Fig. 3(a)), and the system uses the relevant historical agricultural data. This dual-mode design allows the system to be used even where sensors are unavailable or unreliable.

C. Data Collection and Preprocessing

In Sensor Mode, the data are collected using the DHT11 temperature and humidity sensor, the NPK sensor, the soil pH sensor, the soil moisture sensor and the BH1750 light sensor connected to the ESP32. Historical datasets are used when sensor data are not available and also for training and testing the ML models. The collected data are validated, cleaned and preprocessed before analysis, and missing, invalid and abnormal values are handled appropriately. The weather information of the selected location is also displayed in the application (Fig. 3(c)).

D. Machine Learning Models

Four ML models are used, and all of them are developed in Python using scikit-learn, Pandas and NumPy. (1) The *crop recommendation* model uses the soil parameters (N, P, K and pH) and the weather parameters (temperature, humidity and rainfall) and recommends three suitable crops in priority order, each with a score (Fig. 3(d)). (2) The *fertilizer recommendation* model suggests a fertilizer from the crop, its growth stage, the season, the irrigation type, the previous crop, the region, and the fertilizer used and the yield obtained in the last season (Fig. 4(b)). (3) The *yield prediction* model estimates the expected yield for a given area, crop and year (Fig. 4(c)). (4) The *market demand prediction* model uses the Autoregressive Integrated Moving Average (ARIMA) method on historical market data for a selected year, month, region and crop (Fig. 4(a)).

An ARIMA (p, d, q) model can be written as

$$y'_t = c + \varphi_1 y'_{t-1} + \ldots + \varphi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (1)$$

where y'_t is the demand series after d differencing operations, c is a constant, φ_i and θ_j are the autoregressive and moving-average coefficients of orders p and q, and ε_t is the error term. Eq. 1 is fitted to the historical market data and used to forecast the demand for future months.

E. System Workflow

The workflow of the system is shown in Fig. 2. After the start, the system checks the sensor availability. If sensors are available, the sensors are selected, the IoT sensor data are collected, and the available inputs are processed and the sensor readings validated. Otherwise, the farm details (name, region and soil type) are taken from the farmer, the historical agricultural data are loaded and the data are preprocessed. In both cases, the data are passed through preprocessing and the ML models, which perform crop recommendation, fertilizer recommendation, yield prediction and market demand prediction in sequence. Finally, all four predictions are displayed to the farmer.

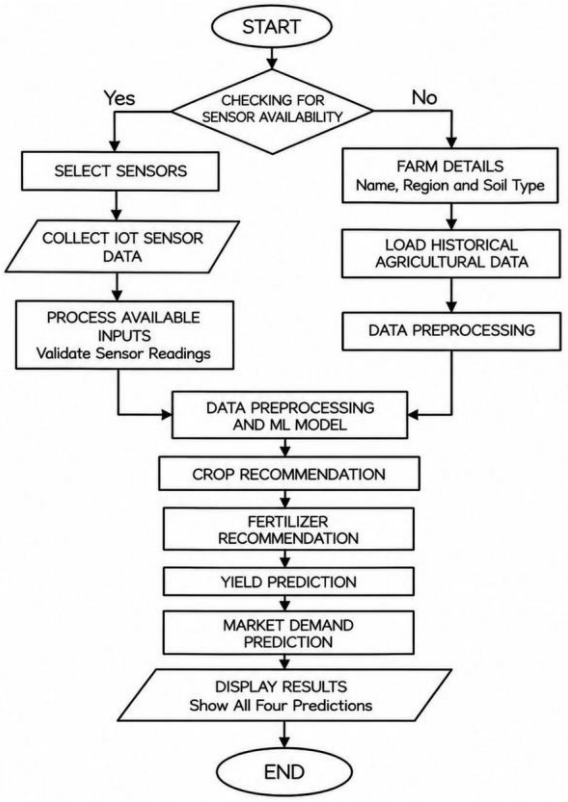

Fig. 2. Flowchart of the proposed system

F. Mobile Application and Cloud Services

The mobile application is developed using Flutter and Dart. It includes splash, login and signup screens, a dashboard, and screens for farm details, sensor setup, weather, crop recommendation, fertilizer recommendation, yield prediction, market demand and the user profile. Firebase is used for user authentication and Cloud Firestore for cloud data storage, and the results of all modules are displayed in the application.

VI. HARDWARE AND SOFTWARE REQUIREMENTS

The hardware and software components used in the system are listed in Table 2.

Table 2: Hardware and software components of the system

Component	Function
Hardware	
ESP32 microcontroller	Main controller with Wi-Fi; reads the sensors and transmits the data
DHT11 sensor	Measures temperature and humidity
NPK sensor	Measures soil nitrogen, phosphorus and potassium
Soil pH sensor	Measures the acidity or alkalinity (pH) of the soil
Soil moisture sensor	Measures the moisture content of the soil

Component	Function
USB power supply, breadboard and jumper wires	Power for the ESP32 and the sensors; prototype connections
Computer/laptop	Programming, development and testing
Software	
Arduino IDE, ESP32 board package and DHT sensor library	Programming the ESP32 and reading the DHT11 sensor
Python (scikit-learn, Pandas, NumPy)	Data processing and ML model development
ARIMA	Time-series forecasting of market demand
Flutter and Dart	Cross-platform mobile application development
Android Studio / Visual Studio Code	Application development, debugging, emulator testing and project management
Firebase (Authentication and Cloud Firestore)	User authentication and cloud data storage
Wi-Fi with HTTP or MQTT	Communication between the ESP32, the backend and the application
Datasets	Training and testing of the ML models

VII. Results and Discussion

A. Mobile Application

The mobile application was implemented and tested, and its main screens are shown in Fig. 3 and Fig. 4. The farm details screen (Fig. 3(a)) collects the farmer name, region and soil type, and the sensor setup screen (Fig. 3(b)) lets the farmer choose between Sensor Mode and Non-Sensor Mode. The weather screen (Fig. 3(c)) shows the temperature, humidity, weather condition and wind speed of the selected location. The crop recommendation screen (Fig. 3(d)) lists the soil and weather parameters and gives the three recommended crops with their priority.

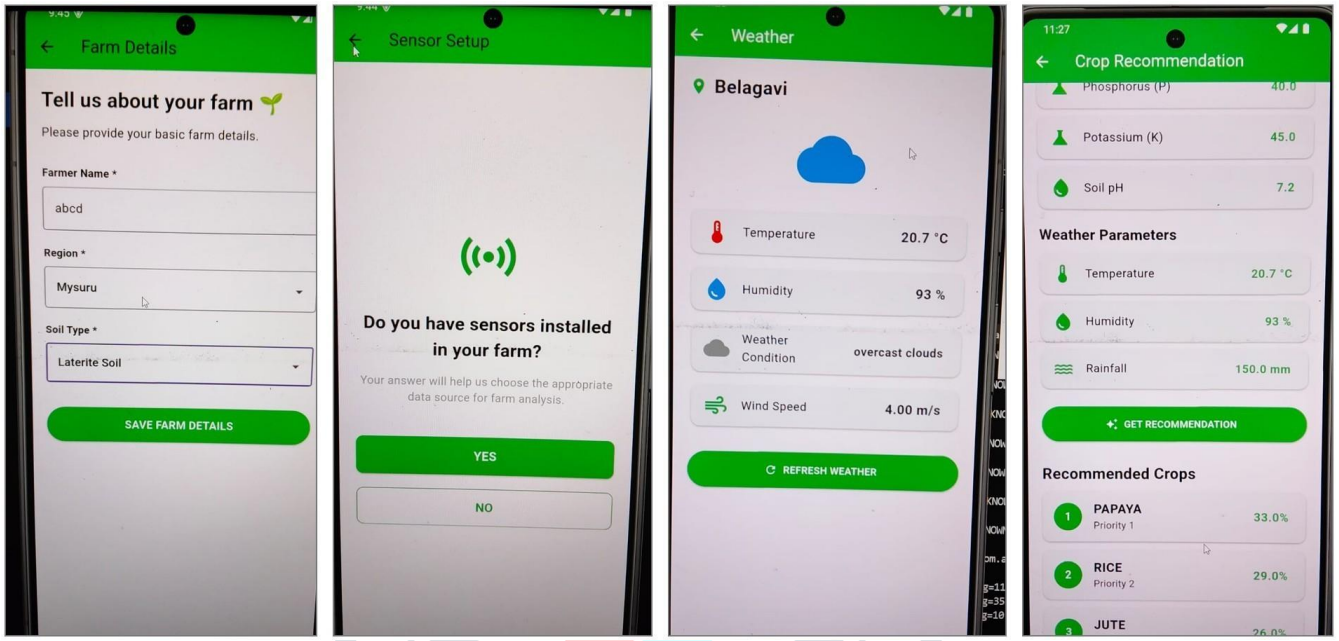

Fig. 3. Screens of the mobile application: (a) farm details, (b) sensor availability selection, (c) weather and (d) AI crop recommendation

The market demand screen (Fig. 4(a)) takes the year, month, region and crop as input. The fertilizer recommendation screen (Fig. 4(b)) takes the crop and field details and displays the recommended fertilizer, and the yield prediction screen (Fig. 4(c)) displays the predicted yield for the selected area, crop and year. Sample outputs of the prototype are given in Table 3.

Table 3: Sample outputs displayed by the prototype

Module	Sample input (as displayed)	Output displayed
Weather	Location: Belagavi	20.7 °C, humidity 93 %, overcast clouds, wind speed 4.00 m/s
Crop recommendation	Phosphorus 40.0, potassium 45.0, soil pH 7.2; temperature 20.7 °C, humidity 93 %, rainfall 150.0 mm	Papaya (33.0 %, priority 1), rice (29.0 %, priority 2), jute (26.0 %, priority 3)
Fertilizer recommendation	Rice; vegetative stage; Kharif season; drip irrigation; previous crop maize; region South; fertilizer used last season 100; yield last season 4.5	NPK
Yield prediction	Area: India; crop: rice; year: 2020	23,162.44 hg/ha
DHT11 sensor (serial monitor)	DHT11 sensor connected to the ESP32	Temperature 31.00, 31.90 and 31.50 °C; humidity 56.00 %; status “VALID”

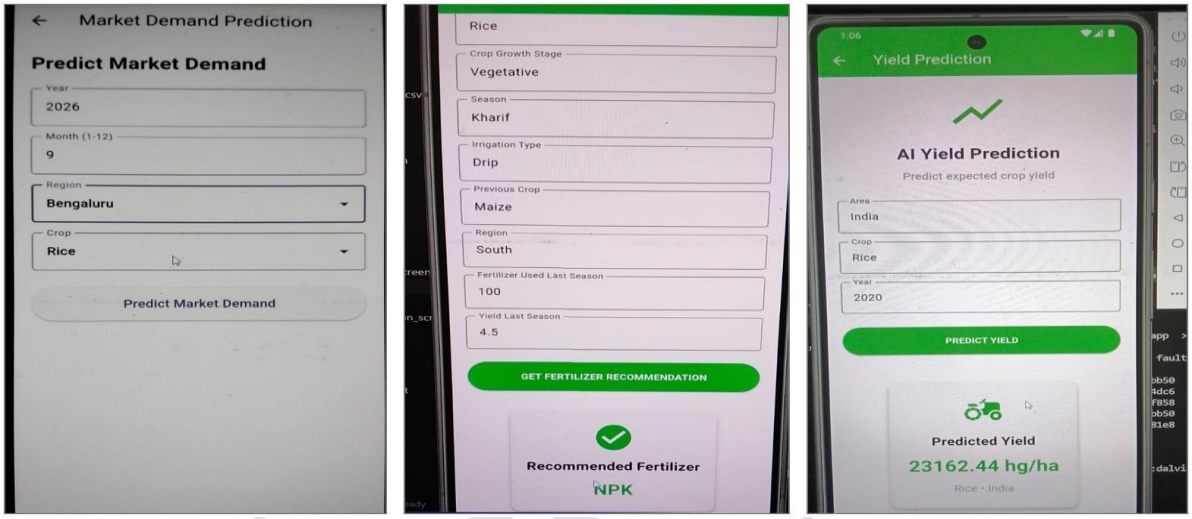

Fig. 4. Screens of the mobile application: (a) market demand prediction input, (b) fertilizer recommendation and (c) yield prediction

B. Sensor Interface

The sensor interface was tested on a breadboard prototype, shown in Fig. 5(a), in which the ESP32 is connected to the DHT11 sensor and a soil sensor probe placed in a soil sample. The program written in the Arduino IDE reads the DHT11 sensor and prints the temperature and humidity on the serial monitor, together with a validity status for each reading (Fig. 5(b)).



Fig. 5. Sensor interface prototype: (a) ESP32 connected to the DHT11 sensor and a soil sensor probe on a breadboard and (b) DHT11 readings on the Arduino IDE serial monitor

C. Discussion

The prototype shows that the four services can be provided through a single mobile application. The dual-mode design lets the system work with real-time sensor readings when they are available and with farm details and historical data when they are not, and the three-crop priority list gives the farmer an alternative if the first crop is not suitable. The outputs in Table 3 are sample outputs of the prototype and are not intended as a performance benchmark. The effectiveness of the system depends on the accuracy of the sensors, the quality of the datasets, the performance of the ML models and the availability of internet connectivity.

VIII. Applications

The proposed system can be used for: (i) crop recommendation based on soil, weather, season and region; (ii) fertilizer management, by suggesting fertilizers from soil nutrients and crop requirements and thereby reducing excess fertilizer usage; (iii) yield forecasting for better planning and allocation of resources; (iv) market trend analysis to identify crop demand and price trends; (v) soil monitoring of moisture, pH, NPK, temperature and humidity; (vi) smart irrigation systems, by analyzing soil moisture and weather conditions; and (vii) precision farming and agricultural advisory platforms that give data-based recommendations and help farmers reduce unnecessary use of fertilizer and other resources.

IX. Conclusion and Future Scope

This paper presented an AI based farming guidance system for Karnataka regions that integrates IoT sensors, ML models, a decision support system and a Flutter mobile application with Firebase. The prototype includes modules for crop recommendation, fertilizer recommendation, yield prediction, market demand prediction and weather information, and it works with either real-time sensor data or historical data. The system aims to improve crop productivity, resource management and overall farming efficiency.

In future work, additional sensors for soil pH, moisture, temperature, humidity and light will be integrated, and the ML models

will be enhanced for more accurate predictions and real-time disease detection. Automated irrigation and real-time alerts through the mobile application will also be implemented, and the models will be evaluated with standard performance metrics on larger regional datasets.

ACKNOWLEDGMENT

The authors thank Dr. Dilip Kumar K, Principal, Dr. P. N. Sudha, Professor and Head of the Department of Electronics and Communication Engineering, and the project coordinators Dr. Rekha N and Mrs. Suma Santhosh, K. S. Institute of Technology, Bengaluru, for their encouragement, support and valuable suggestions.

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