Mridgun – Smart Fertilizer Recommendation System

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Abstract*—Agriculture faces persistent challenges related to inefficient fertilizer usage, declining soil fertility, and environmental degradation caused by excessive chemical inputs. Limited access to real-time soil nutrient information often leads to generalized fertilizer application practices, resulting in reduced crop productivity and sustainability. This paper presents MRIDGUN – Smart Fertilizer Recommendation System, a practical framework that integrates real-time soil NPK (Nitrogen, Phosphorus, and Potassium) sensing with embedded processing, secure backend data management, and analytical support. The system collects soil nutrient data through sensor-based monitoring, validates and stores it for historical analysis, and assists in identifying nutrient imbalance patterns using data-driven techniques. Secure user authentication ensures controlled access to agricultural data, while the system design emphasizes affordability, scalability, and real-world applicability. The conceptualization and refinement of MRIDGUN were influenced by real-world farmer interactions and academic guidance, ensuring practical relevance. Experimental observations indicate that the proposed system provides timely and reliable soil nutrient insights, supporting informed fertilizer application and sustainable agricultural practices.

***Keywords*— Smart Agriculture, Precision Farming, Soil Nutrient Monitoring, Fertilizer Recommendation System, IoT, Machine Learning, Sustainable Agriculture.**

I. INTRODUCTION

Agriculture remains a cornerstone of economic stability and food security, particularly in developing economies where a large population depends on farming for livelihood. However, modern agricultural practices increasingly face challenges related to inefficient fertilizer usage, declining soil fertility, and environmental degradation caused by excessive and imbalanced chemical inputs [17]. Precision agriculture has emerged as a promising approach to address these issues by promoting data-driven and site-specific farming practices [1].

Traditional fertilizer management practices rely primarily on laboratory-based soil testing and generalized agronomic recommendations. Although these methods provide accurate assessments, they are often time-consuming, costly, and impractical for frequent use by farmers. As a result, fertilizer application decisions are commonly based on intuition or prior experience, which may not accurately reflect current soil conditions, leading to reduced crop productivity and increased input costs [6].

Recent advancements in embedded systems, Internet of Things (IoT), and data analytics have enabled the development of smart agriculture solutions capable of monitoring soil conditions in real time [4]. These technologies offer significant potential to improve decision-making by providing continuous access to soil nutrient information. However, many existing solutions are either technologically complex, economically expensive, or designed primarily for large-scale farming operations, limiting their adoption among small and marginal farmers [7], [14].

Furthermore, the integration of machine learning and data-driven decision support systems has enhanced the ability to analyze agricultural data and identify meaningful patterns related to soil health and fertilizer usage [2], [10]. Despite their effectiveness, such approaches often require large datasets and substantial computational resources, which restrict their applicability in field-level deployments [3]. To address these challenges, this paper proposes MRIDGUN – Smart Fertilizer Recommendation System, a practical and scalable solution that integrates real-time soil NPK monitoring with backend data management and analytical support. The system is designed to bridge the gap between advanced agricultural technologies and real-world usability, promoting sustainable fertilizer management and informed decision-making based on actual soil conditions.

II. RELATED WORK

Precision agriculture has gained significant attention as an effective approach for improving crop productivity while minimizing environmental impact. By enabling site-specific and data-driven farming practices, precision agriculture supports optimized use of resources such as water and fertilizers [1]. Several studies emphasize that accurate soil nutrient assessment is a key factor in achieving sustainable agricultural outcomes and reducing excessive fertilizer application [17].

Sensor-based soil monitoring systems have been widely explored to enable real-time assessment of soil parameters. Researchers have proposed the use of NPK sensors, soil moisture sensors, and other environmental sensors integrated with embedded platforms to collect in-field soil data [8], [11]. These systems reduce reliance on laboratory-based soil testing and provide timely insights into soil health. However, challenges related to sensor calibration, deployment cost, and long-term durability in field conditions remain open research concerns.

IoT-based smart farming solutions further enhance soil monitoring capabilities by enabling remote data transmission, centralized storage, and cloud-based analysis [4]. Such systems allow farmers and agricultural stakeholders to access soil information in real time, improving responsiveness and decision-making. Despite these advantages, several studies report limitations related to infrastructure cost, continuous internet dependency, and scalability, particularly in rural and resource-constrained environments [7], [14].

Machine learning and data-driven approaches have also been applied to agricultural decision support, especially for crop and fertilizer recommendation systems. Techniques such as Random Forest and other classification models have demonstrated improved accuracy in fertilizer optimization when trained on historical agricultural datasets [2], [9], [13]. However, these approaches often require large volumes of labeled data and may lack adaptability when real-time soil data is not continuously integrated [3], [10].

Security and data privacy have emerged as important considerations in IoT-based agricultural platforms. Studies highlight the need for secure authentication, controlled data access, and reliable backend services to protect sensitive agricultural and user data [12]. In contrast to existing solutions, the proposed MRIDGUN – Smart Fertilizer Recommendation System adopts a balanced approach that integrates real-time soil nutrient sensing, secure backend data management, and analytical support while maintaining affordability and practical deployability. This approach addresses several limitations identified in prior research and aligns with sustainable agriculture objectives [5], [18].

III. METHODOLOGY

The MRIDGUN – Smart Fertilizer Recommendation System is designed as an end-to-end intelligent framework that integrates real-time soil sensing, embedded data processing, backend data management, and analytical support to assist informed fertilizer decision-making. The methodology focuses on acquiring accurate soil nutrient data, maintaining historical records, and enabling data-driven insights while ensuring practical deployability in real-world agricultural environments.

A. System Architecture

The proposed MRIDGUN – Smart Fertilizer Recommendation System follows a layered system architecture, designed to ensure modularity, scalability, and reliable end-to-end operation. The architecture integrates soil sensing, embedded data processing, backend services, secure authentication, and recommendation logic in a structured manner. The overall layered architecture of the system is illustrated in Fig. 1, which depicts the interaction and data flow between

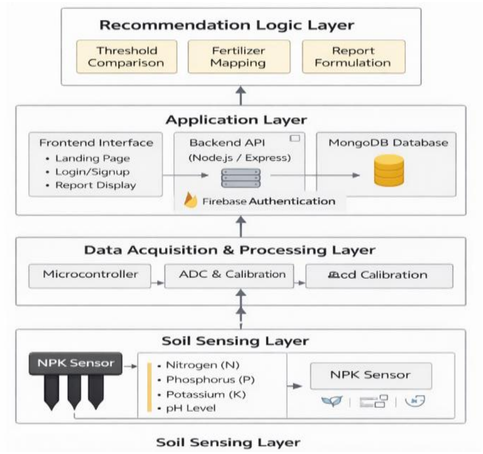

Figure 1. Layered system architecture of the proposed MRIDGUN Smart Fertilizer Recommendation System.

different functional layers. At the lowest level, the Soil Sensing Layer is responsible for acquiring real-time soil nutrient data from the agricultural field. This layer employs an NPK sensor to measure the concentration of essential macronutrients, namely Nitrogen (N), Phosphorus (P), and Potassium (K). These parameters serve as primary indicators of soil fertility and crop nutrient availability. Sensor-based soil monitoring enables in-field assessment of soil conditions and reduces dependency on laboratory-based soil testing methods [8], [11].

The Data Acquisition and Processing Layer consists of the Arduino UNO microcontroller, which interfaces directly with the soil NPK sensor. This layer performs analog-to-digital conversion, sensor calibration, and preliminary data validation to ensure accuracy and consistency of the collected readings. Local preprocessing at this stage helps filter abnormal values and prepares the data for reliable transmission to higher layers, improving system robustness in outdoor agricultural environments [4].

Above this, the Application Layer manages data communication, storage, and user interaction. The backend API, developed using Node.js and Express, receives validated soil nutrient data from the embedded layer and handles business logic and data management. Soil nutrient readings and historical records are stored in a MongoDB database, enabling longitudinal analysis and trend identification. User authentication and access control are handled using Firebase Authentication, ensuring secure and controlled access to system resources and user-specific data [12]. The frontend interface provides functionalities such as login/signup, report visualization, and soil nutrient status display, facilitating user interaction with the system.

At the top level, the Recommendation Logic Layer performs fertilizer-related decision support based on processed soil nutrient data. This layer includes threshold comparison of NPK values against recommended ranges, fertilizer mapping logic to identify appropriate corrective measures, and report formulation to generate user-readable insights. By combining real-time sensor data with backend analytics, this layer supports informed and sustainable fertilizer management decisions [5], [13].

Overall, the layered architecture shown in Fig. 1 enables clear separation of responsibilities across system components, enhances maintainability, and supports future scalability. The modular design allows additional sensors, advanced analytics, or predictive models to be integrated without significant architectural changes, making the system suitable for real-world agricultural deployment.

B. Soil Data Acquisition

Soil data acquisition is the first operational stage of the MRIDGUN system and forms the foundation for subsequent analysis and recommendation. In this stage, real-time soil nutrient data is collected directly from the agricultural field using an NPK sensor. The sensor measures the concentration of essential macronutrients—Nitrogen (N), Phosphorus (P), and Potassium (K)—which play a crucial role in determining soil fertility and crop growth potential. Sensor-based acquisition enables in-field assessment of soil conditions and reduces reliance on laboratory-based soil testing, which is often time-consuming and costly. The use of real-time sensing allows the system to capture dynamic variations in soil nutrient levels caused by factors such as crop uptake, irrigation, and fertilizer application. This continuous and location-specific data collection supports precision agriculture practices by providing accurate insights into actual soil conditions rather than generalized assumptions [1].

C. Data Preprocessing and Validation

Raw sensor data obtained from the field may contain noise, fluctuations, or out-of-range values due to environmental conditions and sensor limitations. To ensure data reliability, the MRIDGUN system performs preprocessing and validation before further processing. This includes sensor calibration, range checking, and filtering of abnormal readings at the embedded and backend levels. Validated data is structured into a standardized format to maintain consistency across records. This preprocessing step ensures that inaccurate or inconsistent data does not propagate into the analytical and recommendation layers, thereby improving the overall accuracy and reliability of the system. Such preprocessing is essential for effective data-driven decision support in smart agriculture systems [4], [10].

D. Data Management and Analytical Processing

Once validated, soil nutrient data is transmitted to the backend system, where it is securely stored in a centralized database. The system maintains historical records of soil nutrient values for each user, enabling longitudinal analysis of soil health over time. Historical data storage plays a key role in identifying recurring nutrient deficiencies, excesses, and long-term soil fertility trends [18]. Analytical processing is applied to both real-time and historical data to interpret soil nutrient status. Data-driven techniques are used to analyze nutrient patterns and support fertilizer-related decision-making. The analytical component is designed to be extensible, allowing integration of advanced machine learning models in the future as data volume increases [2], [13].

E. Recommendation Logic

The recommendation logic forms the core decision-support component of the MRIDGUN system. In this stage, processed soil nutrient values are compared against predefined agronomic threshold ranges to assess nutrient sufficiency or deficiency. Based on this comparison, fertilizer mapping logic is applied to determine appropriate corrective actions. The system formulates a structured report that presents soil nutrient status and fertilizer-related guidance in a user-readable format. This approach ensures that recommendations are grounded in actual soil conditions and supported by analytical insights rather than generalized assumptions. Such targeted fertilizer management contributes to improved crop productivity and sustainable agricultural practices [5].

F. Security and Access Control

Security and data integrity are critical considerations in IoT-based agricultural systems [12]. The MRIDGUN system incorporates secure user authentication mechanisms to ensure controlled access to soil data and analytical results. Only authenticated users are permitted to view or retrieve system-generated information. Backend services enforce strict access control and input validation to prevent unauthorized data access or manipulation. Secure handling of sensor data and user information enhances system reliability and builds trust among users, making the system suitable for real-world deployment in agricultural environments.

IV. EXPERIMENTAL RESULTS

This section presents the experimental observations and discussion related to the implementation of the MRIDGUN – Smart Fertilizer Recommendation System. The evaluation focuses on system functionality, data handling behavior, response characteristics, and practical applicability rather than purely algorithmic accuracy, as the primary goal of the system is real-world soil nutrient monitoring and decision support.

A. Experimental Setup

The experimental setup consists of a sensor-based soil nutrient monitoring unit integrated with an embedded processing device and a backend data management system. Soil nutrient data, specifically Nitrogen (N), Phosphorus (P), and Potassium (K) values, were collected using the NPK sensor deployed in field-like conditions. The embedded unit transmitted validated data to the backend system, where it was stored, processed, and made accessible to authenticated users. The backend infrastructure managed data storage, user authentication, and analytical processing, enabling real-time as well as historical analysis of soil nutrient information. The system was tested under multiple input conditions to observe data consistency, reliability, and end-to-end data flow behavior.

B. Functional Validation

Functional validation was performed to verify the correct operation of each system component and their integration. The system successfully captured soil nutrient readings, transmitted data to the backend, and stored it in the database with proper user association. Authenticated users were able to access soil nutrient information and view processed results without unauthorized access. The recommendation logic correctly evaluated soil nutrient levels against predefined agronomic thresholds and generated appropriate fertilizer-related guidance. This validation confirms that the system performs as intended and supports informed decision-making based on actual soil conditions rather than generalized assumptions.

C. System Performance Analysis

System performance was evaluated in terms of responsiveness, data handling efficiency, and operational stability. The data transmission from the sensing unit to the backend occurred with minimal delay, making the system suitable for near real-time monitoring. Backend processing and data retrieval operations were observed to be efficient, even with repeated data submissions. The modular design of the system contributed to stable operation, as failures or inconsistencies at one layer did not propagate across the entire system. Such performance characteristics are essential for practical deployment in agricultural environments where reliability is a key requirement [7], [14].

D. Discussion on Practical Applicability

The experimental observations indicate that the MRIDGUN system is well-suited for real-world agricultural use, particularly for small and medium-scale farmers. By providing real-time soil nutrient insights, the system enables targeted fertilizer application, which can help reduce fertilizer wastage and improve crop productivity. This aligns with the principles of precision agriculture and sustainable farming practices [1], [5]. The inclusion of historical data storage further enhances decision-making by allowing users to observe soil nutrient trends over time. Such data-driven insights support long-term soil health management and environmentally responsible fertilizer usage [18].

E. Limitations and Observations

While the system demonstrates reliable operation, certain limitations were observed during experimentation. Sensor accuracy may vary depending on soil type, moisture conditions, and calibration quality. Additionally, the current recommendation logic is based on predefined thresholds rather than fully automated predictive models. These limitations highlight opportunities for future enhancement, such as integrating advanced machine learning models, expanding the range of sensed parameters, and improving sensor calibration techniques. Despite these limitations, the system effectively fulfills its intended objective of providing practical and reliable soil nutrient insights.

V. CONCLUSION AND FUTURE WORK

This paper presented MRIDGUN — Smart Fertilizer Recommendation System, an end-to-end solution designed to support informed fertilizer management through real-time soil nutrient monitoring and data-driven analysis. The proposed system integrates soil NPK sensing, embedded data processing, secure backend services, and analytical logic within a layered architecture to provide reliable and practical soil nutrient insights. By focusing on real-time data acquisition and historical nutrient tracking, the system addresses limitations of traditional fertilizer management practices and promotes precision agriculture.

Experimental observations demonstrate that the system operates reliably in acquiring, processing, and presenting soil nutrient information, enabling targeted fertilizer-related decision support. The modular design, secure access control, and emphasis on affordability make MRIDGUN suitable for deployment in real-world agricultural environments, particularly for small and medium-scale farmers. The system aligns with sustainable agriculture principles by encouraging optimized fertilizer usage and reducing unnecessary chemical input.

Future work will focus on enhancing the analytical capabilities of the system through the integration of advanced machine learning models for predictive fertilizer recommendation and crop-specific guidance. Additional soil parameters such as moisture and pH may be incorporated to improve recommendation accuracy. Further scalability can be achieved by supporting larger datasets, mobile application interfaces, and automated fertilizer dispensing mechanisms. These enhancements will strengthen the system's potential as a comprehensive smart agriculture platform.

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