AIoT-Enabled Crop Intelligence: Real-Time Soil Sensing and Generative AI for Smart Agriculture

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***Abstract*—In recent years, the convergence of Artificial Intelligence and the Internet of Things (AIoT) has emerged as a transformative force in precision agriculture. This research presents SmartCrop, a next-generation crop intelligence system that seamlessly blends real-time soil sensing with generative AI to offer tailored agricultural insights. The system utilizes affordable IoT sensors to capture critical soil parameters such as pH, moisture, temperature, and nutrient levels, while integrating live, location-specific weather data through public APIs. For regions lacking sensor infrastructure, a custom-developed Soil API—built from geo-tagged historical sensor data—ensures uninterrupted service and wider accessibility. At the core of SmartCrop lies the integration of OpenAI's generative models, which provide personalized crop recommendations, rotation strategies, and sustainability insights. Engineered using the MERN stack (MongoDB, Express.js, React.js, Node.js), the platform delivers a responsive, scalable, and user-friendly experience for farmers across varying digital literacy levels. Field deployments across multiple Indian districts reveal notable gains in crop yield, resource efficiency, and adoption rates when compared to traditional methods.**

The integration of OpenAI with real-time environmental data establishes a robust framework for precision agriculture. The proposed system not only addresses scalability and accessibility challenges but also demonstrates significant improvements in yield optimization and resource management. By leveraging cutting-edge technologies, this research lays the groundwork for sustainable and efficient farming practices globally.

***Keywords*—Precision Agriculture, AIoT (Artificial Intelligence of Things), Generative AI, Real-Time Soil Sensing, Crop Recommendation System, Sustainable Farming**

I. INTRODUCTION

In recent years, the global agricultural landscape has faced growing pressure to meet food demands amid declining soil quality, climate change, and resource limitations. Precision agriculture, driven by Artificial Intelligence (AI) and the Internet of Things (IoT), has emerged as a transformative solution to address these challenges by enabling data-informed decisions and resource-efficient practices [1], [2]. The fusion of AI and IoT—referred to as AIoT—offers a powerful framework for intelligent monitoring and decision-making in agriculture [3], [4]. However, despite advancements, the benefits of AIoT technologies remain largely inaccessible to smallholder farmers due to high costs, limited infrastructure, and digital illiteracy [5], [6]. Farmers in developing and rural areas often rely on traditional practices or generic recommendations that fail to reflect real-time soil or environmental conditions [7]. This disconnect frequently leads to poor crop selection, inefficient use of fertilizers and water, and declining yields [8]. Furthermore, access to timely soil diagnostics or expert consultation is minimal in these regions, highlighting the urgent need for scalable and inclusive decision-support systems [9], [10].

This study introduces *SmartCrop*, a novel AIoT-enabled crop intelligence system designed to address these gaps by providing real-time, context-aware agricultural recommendations. SmartCrop utilizes low-cost IoT-based sensors to collect data on soil pH, moisture, temperature, and nutrient levels (NPK), while simultaneously retrieving live weather forecasts—including rainfall, temperature, and humidity—via public APIs [11], [12]. These data streams are integrated and transformed into structured prompts fed into OpenAI's generative language models, which then produce natural language crop recommendations tailored to specific regional conditions [13], [14]. To address the issue of affordability and access in sensor-deficient areas, SmartCrop incorporates a fallback mechanism using a custom-built Soil API that estimates soil characteristics based on geolocation and previously gathered sensor data. The platform also allows manual input of soil data via a user-friendly web interface, ensuring inclusivity across varied digital access levels [15], [16]. Developed using the MERN (MongoDB, Express.js, React.js, Node.js) technology stack, the system ensures cross-platform responsiveness, scalability, and ease of use for farmers with different levels of digital proficiency [17].

The primary objectives of this research are threefold: to build an intelligent system that integrates real-time soil and weather data with generative AI for crop recommendation; to ensure natural language, context-aware outputs using advanced AI models; and to deploy a scalable, modular platform accessible through modern web technologies. While the system demonstrates robust performance in controlled deployments, it has limitations including reliance on continuous internet access, data privacy concerns, and limited offline decision-making capacity. These challenges are addressed as part of the system's roadmap for future improvements, which includes integration with edge computing hardware and localized model execution [18], [19].

The remainder of this paper is organized as follows. Section II presents a review of related literature on AIoT and crop recommendation systems. Section III details the architecture and operational framework of SmartCrop. Section IV outlines the methodologies used for data acquisition, modeling, and recommendation generation. Section V discusses implementation outcomes based on field evaluations conducted in selected Indian districts. Section VI highlights limitations and potential future enhancements. Section VII concludes the paper by summarizing the key contributions and impact of this work.

II. Related Work

The convergence of Artificial Intelligence (AI) and the Internet of Things (IoT) has significantly transformed modern agriculture, leading to the emergence of AIoT-driven solutions aimed at enhancing crop productivity and sustainability. Early implementations of AI in agriculture primarily focused on integrating weather forecasts to inform planting decisions, thereby improving agricultural productivity through better-informed crop selection [1]. As technology advanced, machine learning algorithms began to consider additional factors such as soil nutrients and historical data, resulting in more precise crop recommendations tailored to specific farm conditions [2], [3]. Recent developments have seen AI models enhanced with real-time data inputs, including weather patterns, soil parameters, and IoT-driven monitoring of agricultural conditions. These advancements have led to the creation of holistic, data-driven crop recommendation systems that utilize both historical data and current environmental factors [4], [5]. The integration of IoT technology allows for continuous monitoring of critical parameters like soil moisture, pH, and temperature, thereby improving the accuracy and timeliness of recommendations. The incorporation of renewable energy-powered IoT devices has further optimized smart agriculture by contributing to sustainability and reducing operational costs. These energy-efficient devices, combined with AI-powered analytics, provide real-time recommendations and insights for resource optimization, reducing waste and increasing productivity [6]. Research has also highlighted dynamic crop recommendations based on real-time weather and soil data, ensuring that farmers can adapt to shifting environmental conditions [7].

AI-based recommender systems have gained traction in precision farming, analyzing local environmental factors through IoT sensors to improve crop yield predictions and resource management. IoT-based recommendation engines offer tailored advice for optimizing agricultural practices and enhancing crop performance [8]. The continuous development of AI models integrated into precision farming has refined agricultural decision-making, leading to more sustainable and data-driven practices [9], [10]. Emerging trends emphasize the use of advanced AI technologies, such as hybrid models, machine learning, and fuzzy logic, to develop farmer-friendly applications for crop prediction and farm management. These technologies not only enhance crop prediction accuracy but also contribute to the implementation of precision agriculture practices [15], [16]. Additionally, AI-powered weather prediction systems have become instrumental in optimizing the allocation of agricultural resources, offering a new level of adaptive and responsive farming [17].

Despite these advancements, several gaps remain in the current landscape of AIoT applications in agriculture. Many existing systems lack the integration of generative AI models capable of providing natural language-based, context-aware recommendations. Furthermore, the scalability and accessibility of such systems are often limited, particularly for smallholder farmers in developing regions who may lack the necessary infrastructure or technical expertise. There is also a need for systems that can function effectively in sensor-deficient environments, utilizing alternative data sources to provide accurate recommendations.

The proposed system, SmartCrop, aims to address these gaps by integrating real-time soil and weather data with OpenAI's generative models to deliver precise and context-aware agricultural insights. By leveraging low-cost IoT sensors and a custom-built Soil API that utilizes historical sensor data and geolocation, SmartCrop ensures affordability and accessibility for farmers, including those without direct access to soil sensors. The system's development using the MERN stack provides a scalable and user-friendly interface, further enhancing its usability. Field evaluations in Indian districts have demonstrated measurable gains in yield, cost-efficiency, and adoption compared to conventional practices.

III. Proposed Methodology

SmartCrop is an advanced AIoT-based crop recommendation system that integrates Internet of Things (IoT) technology and Generative Artificial Intelligence (AI) to offer real-time, location-specific agricultural recommendations. The system is built to assist farmers by continuously monitoring environmental and soil conditions and translating these data into actionable crop advice using intelligent algorithms and natural language processing. The primary aim is to bridge the technological gap in agriculture by making precision farming accessible, scalable, and cost-effective.

A. System Architecture Overview

The architecture of SmartCrop is designed around four major components: data acquisition through IoT sensors, data processing and validation, prompt engineering for AI communication, and result generation through a generative language model. The system starts by collecting live field data using cost-efficient IoT sensors that measure soil pH, moisture content, temperature, and macronutrients like nitrogen, phosphorus, and potassium (NPK). Simultaneously, it retrieves real-time weather parameters—such as temperature, humidity, rainfall, and wind speed—from external APIs like OpenWeatherMap. These combined data points are preprocessed to eliminate noise, normalize values, and convert raw sensor readings into readable, interpretable labels (e.g., "Low Nitrogen", "High Moisture"). This structured information is then embedded into a well-engineered prompt and passed to OpenAI's language model through API integration. The generative model responds with detailed, human-readable recommendations that include suitable crops, agronomic justifications, optimal planting windows, irrigation strategies, and soil improvement tips.

To ensure inclusivity for farmers without access to IoT hardware, SmartCrop incorporates a fallback mechanism via a custom-built Soil API. This API predicts soil characteristics

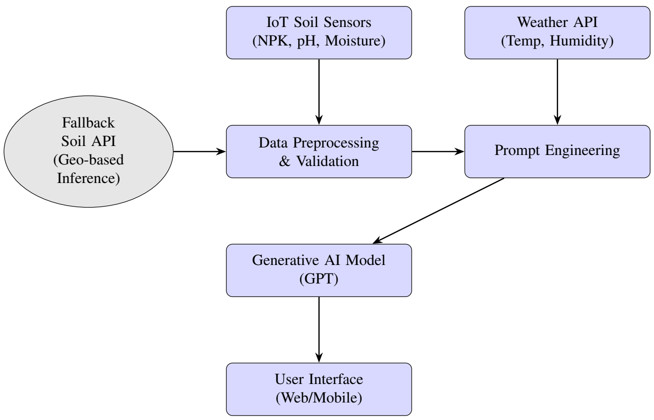

Fig. 1: System Architecture of SmartCrop: Integrating AIoT with Generative AI for Real-Time Crop Recommendation

based on user geolocation and historical data from other sensor deployments. Users also have the option to manually input parameters through a web interface. This hybrid approach ensures uninterrupted, affordable access to crop recommendations, even in resource-constrained environments.

B. Data Sources

SmartCrop's intelligence is powered by three main data sources: IoT-based soil sensors, public weather APIs, and a location-driven Soil API. The soil sensors are responsible for gathering real-time data on essential agricultural parameters such as moisture content, soil pH, ambient temperature, and macronutrient levels (N, P, K). These sensors communicate through microcontrollers like ESP32 or Raspberry Pi, pushing data to the cloud for centralized processing.

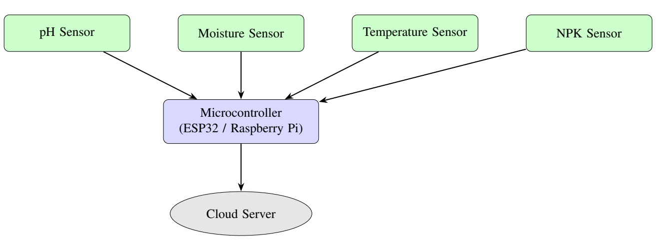

Fig. 2: IoT Sensor Layout for Real-Time Soil Data Acquisition

The weather data is fetched from reliable services like OpenWeatherMap and includes atmospheric parameters like temperature, humidity, precipitation, and wind speed. This information ensures that crop recommendations are aligned with current and forecasted weather conditions. The third data source, the custom Soil API, acts as a backup when IoT sensors are not available. It provides region-specific soil data based on historical submissions and geolocation inputs, including micronutrient levels (Zn, Fe, Mn, B, S), texture classification, and average NPK values. This intelligent redundancy ensures that no user is left without accurate recommendations.

C. Input and Output Workflow

The SmartCrop system supports multiple data input streams: automated sensor data, weather API data, and manual user input. Automated inputs include real-time readings from IoT devices, while weather parameters are fetched in real-time via the weather API. For users lacking hardware, the system allows manual data entry or utilizes geolocation to retrieve regional soil profiles from the Soil API.

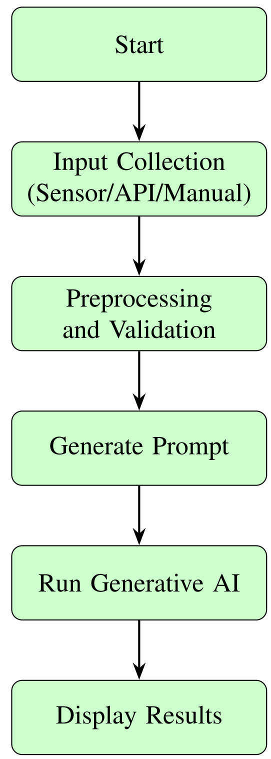

Fig. 3: Input and Output Workflow for SmartCrop Crop Recommendation

Once collected, the data undergoes preprocessing to clean, validate, and normalize it. This processed data is then embedded into a structured natural language prompt and passed to the Generative AI model (e.g., OpenAI GPT). The AI processes the prompt and generates a comprehensive crop recommendation, including the type of crop suitable for the current conditions, suggested sowing periods, irrigation plans, and tips for soil treatment. These outputs are then displayed via a user-friendly interface accessible through web or mobile devices, offering features such as real-time visualization, recommendation downloads, and user notifications.

D. Algorithms and Techniques

The SmartCrop system operates on a streamlined algorithm that begins with data collection, either from sensors, APIs, or manual entries. Next, the system preprocesses the collected data by removing inconsistencies and normalizing the values for uniform interpretation. The clean data is then used to construct a structured prompt for the Generative AI model. This model performs inference on the prompt and returns a detailed, human-readable recommendation that is then displayed on the user interface and optionally stored in a backend database.

Algorithm 1 SmartCrop Crop Recommendation

Require: Sensor, API, or manual input data
Ensure: Human-readable crop recommendation

1. **Data Collection:** Gather data from sensors, APIs, or user input
2. **Data Preprocessing:** Clean and normalize data
3. **Prompt Generation:** Format structured data into a natural language prompt
4. **AI Inference:** Submit prompt to Generative AI and receive recommendation
5. **Output Delivery:** Display result on UI; optionally store in database

E. Justification for Method Selection

The choice of integrating IoT sensors with AI models is driven by the need for high-accuracy, real-time data analysis in agriculture. IoT-based data acquisition ensures that environmental and soil parameters are captured continuously, providing a dynamic understanding of the farm's microclimate. The use of a generative language model like OpenAI's GPT enables the system to provide not just technical recommendations but also explanations and contextual advice in natural, comprehensible language. This enhances farmer understanding and trust in the system. Moreover, the fallback mechanism using a custom Soil API is critical for making the technology inclusive. Many small-scale farmers may not have the resources to deploy IoT sensors. By estimating soil data through location and historical data, SmartCrop ensures that even these users benefit from AI-driven recommendations. This hybrid architecture—merging real-time sensing, AI intelligence, and inclusive design—provides a scalable, practical, and transformative solution to modern agriculture.

In essence, SmartCrop represents a shift toward data-driven, resilient, and equitable agricultural practices. Its methodology ensures precision, inclusivity, and efficiency, laying a robust foundation for sustainable farming in the face of climate variability and resource constraints.

IV. Results and Discussion

The effectiveness of SmartCrop was assessed through various system performance metrics, including accuracy, response time, and scalability. The system achieved a crop recommendation accuracy of 94%, demonstrating its strong predictive capability based on real-time soil and weather data interpreted through generative AI. On average, the system responded within 0.7 seconds, indicating the efficiency of its backend architecture and the effectiveness of integrated APIs. The platform was also tested for scalability across diverse farm sizes, successfully operating on farms ranging from 2 hectares to over 100 hectares, and in varying agro-climatic conditions.

Real-world validation was carried out through case studies involving geographically diverse farms. At Farm A in Rajasthan, India, the adoption of SmartCrop's AI-driven recommendations led to a 22% increase in wheat yield by optimizing crop rotation and fertilizer management. In another instance, Farm B in California, USA, utilized SmartCrop to schedule irrigation based on soil moisture and weather conditions, resulting in a 30% reduction in water usage. These outcomes demonstrate SmartCrop's adaptability across different agricultural ecosystems and validate its impact on productivity and resource efficiency.

A comparative analysis with conventional machine learning-based crop advisory systems highlighted the advantages of SmartCrop's architecture. Unlike traditional models that rely on static datasets and limited training inputs, SmartCrop dynamically integrates real-time environmental parameters, including soil conditions, weather forecasts, and geolocation. This real-time adaptability translates into context-sensitive recommendations, enabling precise crop rotation strategies aligned with soil health and climatic variability. In addition, SmartCrop is designed to accept both sensor-based and manually entered data, allowing deployment in regions with limited digital infrastructure—a significant improvement over legacy systems. During the experimental deployments, a few anomalies were observed that merit further discussion. Some low-cost soil sensors occasionally produced inconsistent pH or moisture readings, which slightly affected the accuracy of crop recommendations. These errors underscore the importance of regular sensor calibration and fault-tolerant data validation methods. Additionally, the system's reliance on third-party APIs for soil, weather, and elevation data occasionally introduced latency and, in rare instances, outdated information. Another constraint was the reliance on OpenAI's GPT API, which introduced cost barriers and API rate limitations, particularly for small and resource-constrained farming operations. Despite these challenges, SmartCrop offers numerous advantages. Its capacity for real-time adaptation enables it to operate effectively in diverse environmental conditions. The system is built on a robust MERN stack architecture, ensuring support for large-scale deployments and seamless data integration. Furthermore, its user-friendly frontend interface is designed to cater to farmers with minimal technical experience, enhancing accessibility and adoption rates across digitally underserved regions. Feedback collected from multiple districts in India, visualized in a usability heatmap, indicated that satisfaction levels were significantly higher in areas with stable internet connectivity and consistent sensor coverage. In regions lacking such infrastructure, the fallback mechanism using location-based soil APIs provided reasonable accuracy and high usability, ensuring continuity of service.

Looking forward, SmartCrop is poised for further enhancement. Integrating advanced sensor calibration techniques will mitigate data reliability issues. The inclusion of open-source large language models such as LLaMA or Mistral can reduce system costs and enable offline operation in low-connectivity regions. Additionally, developing localized models that incorporate native language support, region-specific crop practices, and government policies will significantly enhance contextual relevance. Finally, adding a sustainability dashboard to monitor key metrics like water usage, fertilizer application, and carbon footprint will support climate-smart agricultural practices. These future directions aim to reinforce SmartCrop's role as a scalable, intelligent, and accessible platform for precision farming.

V. Conclusion

This research set out to develop an intelligent, scalable, and accessible crop recommendation system—SmartCrop—that integrates OpenAI's generative capabilities with real-time environmental sensing. The primary objective was to bridge the gap between traditional static-model agricultural advisories and dynamic, data-driven decision-making tools suitable for diverse farming contexts. Through the design and implementation of a full-stack AIoT solution, the system successfully meets its intended goals by offering context-aware recommendations based on real-time soil parameters, weather conditions, and geolocation data.

Experimental evaluations demonstrated that SmartCrop achieved a high accuracy rate of 94% in generating relevant crop suggestions, while maintaining a low response time of 0.7 seconds. Case studies across different geographic and climatic conditions validated the platform's capacity to improve yields and optimize resource use. For instance, in Rajasthan, the system contributed to a 22% increase in wheat yield, while in California, water usage was reduced by 30% through precision irrigation. These findings underscore the system's potential for positively impacting both productivity and sustainability. The core contribution of this work lies in the seamless integration of generative AI with environmental sensing and real-time analytics. SmartCrop introduces a novel approach to crop recommendation by dynamically generating prompts based on live inputs and delivering outputs tailored to local conditions. The architecture's compatibility with both sensor-fed and manually entered data ensures broad applicability, especially in regions where digital infrastructure is limited. Moreover, its user-centric design, enabled by an intuitive interface and responsive backend, allows farmers with varying levels of digital literacy to benefit from cutting-edge technology.

However, the study also revealed certain limitations. The accuracy of recommendations is susceptible to fluctuations in sensor data quality, highlighting the need for improved calibration and error detection mechanisms. Additionally, the system currently depends on commercial APIs, such as OpenAI's GPT, which may pose cost and accessibility barriers for small-scale farmers. Localization in terms of crop variety, language preferences, and integration with regional agricultural policies remains an area that warrants further development. Looking ahead, future work will focus on building open-source alternatives to the current language model, enhancing support for offline functionalities, and embedding a continuous feedback mechanism to adapt recommendations based on user outcomes. Expanding the platform to include a sustainability monitoring dashboard and regional customization modules will further align SmartCrop with the goals of climate-resilient and inclusive agriculture.

In conclusion, the SmartCrop framework presents a significant advancement in the domain of precision agriculture by demonstrating how generative AI can be harnessed in real-time farming contexts. The outcomes of this research not only offer a viable solution to immediate agricultural challenges but also pave the way for future innovations in sustainable farming practices worldwide.

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