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Ferticast - Data-Driven Fertilizer Optimization System Embedded with Rainfall Prediction

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Abstract: This paper introduces a machine learning based fertilizer recommendation system created to help farmers make better and more informed decisions about nutrient application. The system studies key factors such as soil condition, rainfall behavior, and local weather to estimate the right amount of nutrients required for healthy crop growth. It uses Random Forest Regression and time-based analysis to understand patterns and provide reliable recommendations. By including rainfall prediction, the system also helps reduce nutrient loss caused by heavy rain and improves the overall efficiency of fertilizer use. The platform is available through a simple web interface where farmers can enter their crop type and location to receive accurate and timely suggestions. The proposed approach supports modern, data driven farming and promotes the responsible use of fertilizers for sustainable agriculture.

Keywords: machine learning, fertilizer recommendation, rainfall prediction, random forest, soil nutrients, sustainable agriculture.

I. INTRODUCTION

Agriculture plays a central role in global food security and economic development, especially in regions where farming is the primary source of livelihood. Ensuring sustainable crop production requires balanced soil fertility management, yet long-term studies show that continuous or imbalanced fertilization can disrupt nutrient cycles and reduce soil health over time [1]. Determining accurate nutrient requirements is challenging because fertilizer needs vary widely across crops, regions, and weather conditions. For example, optimal NPK levels differ significantly depending on climatic zones and soil types, making precise estimation essential for improving productivity [2]. In addition, fluctuations in rainfall can influence nutrient leaching, soil microbial activity, and the overall fertilizer response of cropping systems [3], while crop rotation practices further affect long-term soil quality and ecosystem resilience [4]. As agriculture moves toward data-driven decision-making, machine learning has emerged as a powerful tool for analyzing factors that influence crop performance and fertilizer efficiency. Recent studies have shown that supervised learning techniques can identify the key variables controlling crop yield and nutrient demand across diverse environments [5]. Rainfall-based prediction models also demonstrate potential in forecasting crop production and assessing fertilizer risk during extreme weather events [6]. Beyond environmental factors, farmer behavior—including risk preferences—also affects fertilizer consumption patterns, leading to inefficiencies in input use [7]. Several machine learning approaches have been explored to improve nutrient estimation and yield prediction. Conditional Random Forests have proven effective in modeling complex soil–crop interactions in long-term field experiments [8], while advanced deep learning and ensemble models have been applied to agricultural decision systems across multiple countries [9], [10]. Improving soil nutrient classification accuracy through automated learning techniques further supports precise fertilizer recommendations at the field level [11]. Recent advancements integrate soil data, crop characteristics, weather variables, and remote-sensing information to deliver robust, data-driven advisory systems for farmers [12]–[15]. The growing shift toward precision agriculture has also led to the development of intelligent tools and IoT-enabled systems for real-time nutrient monitoring and recommendation [13], [16]. Studies evaluating the reliability of machine learning-based fertilizer recommendations confirm that these models can outperform traditional methods in both accuracy and adaptability [17], [18]. Emerging research highlights the importance of integrating soil nutrient data with rainfall patterns and seasonal forecasts to build sustainable and resilient fertilizer advisory systems [19], [20]. Moreover, modern frameworks now focus on optimizing fertilizer inputs alongside yield prediction to reduce environmental impacts while maximizing production [21]. Public datasets, such as the widely used crop recommendation dataset hosted on Kaggle [22], have further accelerated model development by providing standardized inputs for training and evaluation. Overall, the literature indicates a clear progression toward smart and sustainable fertilizer management systems powered by machine learning. This review consolidates existing research in the field, evaluates the strengths and limitations of different modeling approaches, and highlights emerging opportunities for developing reliable, farmer-centric fertilizer recommendation systems.

II. LITERATURE SURVEY

A. Traditional Fertilizer Recommendation Approaches

First, Early approaches to fertilizer recommendation primarily relied on empirical methods and expert agronomist knowledge. Soil testing and crop response experiments formed the backbone of these systems, providing localized guidance based on soil nutrient content and crop requirements [4], [7]. While these methods offered practical insights, they were often limited in scalability, time-consuming, and prone to variability due to environmental factors such as rainfall, temperature, and soil heterogeneity [5]. Moreover, traditional models typically did not account for dynamic interactions between multiple nutrients, leading to suboptimal recommendations in complex cropping systems [6].

B. Machine Learning-Based Models

The template is used to format your paper and style the text. All margins, column widths, line spaces, and text fonts are prescribed; please do not alter them. Recent advances in machine learning (ML) have enabled the development of data-driven fertilizer recommendation systems. Techniques such as Random Forest, Support Vector Machines, and Neural Networks have been employed to model nonlinear relationships between soil parameters, weather conditions, and crop yield [9], [12]. For instance, Random Forest has been shown to handle high-dimensional soil and environmental data effectively, providing robust predictions even in heterogeneous conditions [10]. Similarly, deep learning models, particularly Long Short-Term Memory (LSTM) networks, have been applied to capture temporal dependencies in crop growth and nutrient uptake patterns [14], [16]. These ML-based models not only improve prediction accuracy but also offer adaptive capabilities for different regions and cropping systems.

C. Hybrid and Decision Support Systems

To enhance practical applicability, several studies have integrated ML models with decision support systems (DSS) for real-time fertilizer recommendations [13], [17]. Hybrid systems often combine expert rules, crop simulation models, and ML predictions to provide comprehensive guidance tailored to both farmer needs and environmental sustainability goals [18]. Such systems can recommend precise fertilizer doses, timing, and nutrient combinations while minimizing the risk of nutrient runoff and soil degradation. Notably, platforms leveraging cloud computing and mobile applications have made these tools accessible to farmers in remote areas, bridging the gap between advanced analytics and field-level implementation [19], [20].

D. Challenges and Limitations

Despite notable progress, existing fertilizer recommendation models face several challenges. Data scarcity, inconsistent soil quality measurements, and limited historical crop yield records can reduce model reliability [21]. Furthermore, many ML models remain computationally intensive, making them less feasible for deployment in resource-constrained environments. Integrating multi-source data, ensuring interpretability for non-technical users, and validating models across diverse agroecological zones remain active research areas [8], [15]. Addressing these limitations is critical for developing practical, scalable, and user-friendly fertilizer recommendation systems.

III. PROPOSED SYSTEM AND METHODOLOGY

FertiCast is designed as a smart fertilizer advisory tool that changes recommendations based on upcoming rainfall. Instead of providing one fixed fertilizer value for every crop, it adjusts N, P and K requirements according to the current climate. Rainfall is a major reason why fertilizer efficiency drops, as heavy showers wash away nutrients like nitrogen and potassium from the soil [3]. The way fertilizer reacts to changing weather over many years also proves that static fertilizer charts are not reliable [1]. To solve this issue, FertiCast uses machine learning to estimate nutrient demand and combines it with rainfall checks before advising farmers to apply fertilizers. Machine learning ensemble techniques are suitable for agriculture because they can handle unpredictable soil and weather variation and still make accurate predictions [8], [10]. To ensure farmers can easily access such intelligent decisions, the system is delivered through a web-based platform. This aligns with modern agriculture support systems that rely on mobile or cloud-based advisory services rather than lab tests or expensive tools [16]. Systems using cloud or IoT connectivity also report better precision in farming guidance and resource planning [13].

A. System Architecture Overview

FertiCast (shown in Fig. 3.2.1) works through four main layers:

1) User Input Module – the farmer selects the crop, state and city.
2) Weather Intelligence Module – gathers rainfall probability, rainfall quantity, temperature, and humidity through API.

3) Machine Learning NPK Estimator – predicts nutrient values using a regression ensemble model.
4) Rainfall Decision Engine – verifies whether fertilizer can be applied safely.

Integrating weather data is essential because nutrient needs of the same crop differ under different climate and soil-water conditions [2], [19]. This architecture supports self-operating fertilizer advice that adapts automatically to changing environmental patterns [20].

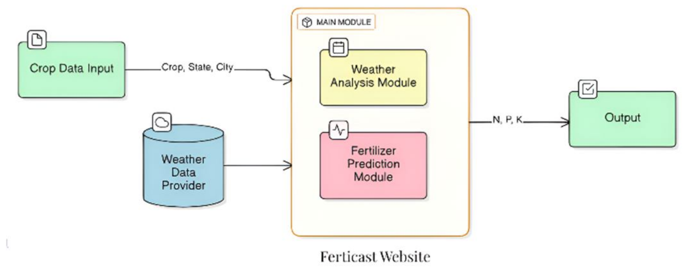

Fig. 3.1 Ferticast Architecture Diagram

B. *Data Acquisition and Preprocessing*

FertiCast uses open agricultural datasets such as the Crop Recommendation Dataset [22]. However, this data must be simplified because soil reports alone are not enough when rainfall directly affects nutrient behavior. Climate-sensitive features like humidity, rainfall and temperature are kept, and crop names are encoded to make them usable for ML models. Crop rotation and past soil nutrient use cause long-term nutrient imbalance [4], which is why keeping fewer but more relevant features improves accuracy. Nutrients wash out faster when rain and humidity rise, so these features are prioritized in preprocessing [3].

Data cleaning, normalization and label encoding are applied similar to the preprocessing used in automated nutrient classification research [11].

The following diagram (Fig. 3.2.2) explains how user input, weather data, machine learning prediction, and rainfall decisions flow within the system:

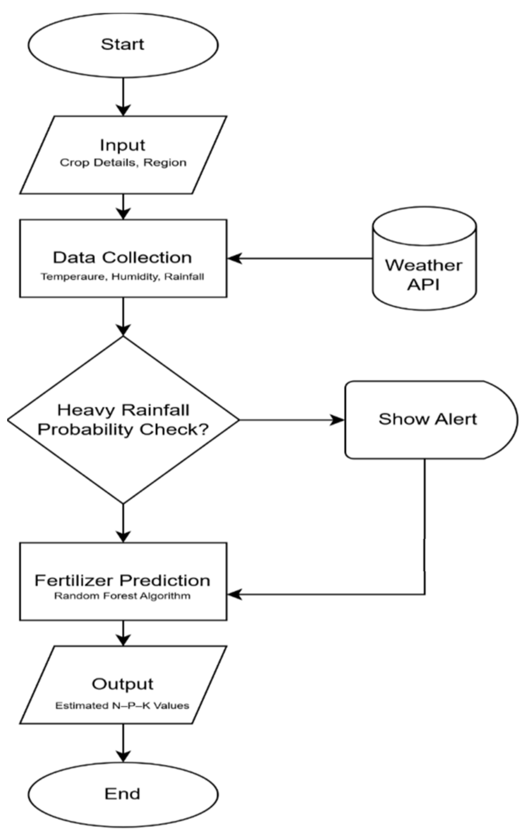

Fig. 3.2 DFD of Ferticast

C. Machine Learning NPK Prediction Model

FertiCast uses Random Forest Regression, which creates multiple decision trees and combines them to give more stable predictions [8]. In fertilizer recommendation studies, such ensemble models consistently perform better than traditional single-model approaches [17], [18], [21]. The model predicts values for N, P and K based on weather sensitivity:

1) Nitrogen demand changes due to losses caused by moisture and runoff [1].
2) Phosphorus uptake depends on climate-controlled soil processes [4].
3) Potassium is the fastest to leach when rainfall is high [3].

Because each nutrient responds differently to climate, the recommended values are not constant. They change depending on where and when the crop is grown.

Table 3.3 Random Forest Regression Algorithm

Step	Description
Step 1	Load the crop nutrient dataset and divide it into training (80%) and testing (20%) sets.
Step 2	Apply preprocessing: encode crop names and normalize features if necessary.
Step 3	Select Random Forest Regression with n_estimators = 50.
Step 4	Train three separate models: one each for Label_N, Label_P and Label_K.
Step 5	Randomly generate multiple Decision Trees using different subsets of data and features.
Step 6	Each tree predicts nutrient values independently.
Step 7	Compute the final output as the average of predictions from all trees.
Step 8	Return the predicted N, P and K values for the selected crop and present weather conditions.

D. Rainfall-Dependent Fertilizer Advisory Module

Before allowing fertilizer application, FertiCast evaluates rainfall conditions. If rainfall exceeds 8 mm/day, fertilizer gets washed away too quickly, especially nitrogen and potassium [3]. If rainfall continues for several days and crosses 12.7 mm/week, soil loses nutrients gradually and plants are unable to absorb them properly [1]. Rainfall forecasting models in agriculture significantly improve the timing of fertilizer application by avoiding such losses [6]. Using weather prediction for fertilizer decisions helps protect nutrients under uncertain climate events [19], [20].Thus, the system follows these actions:

Table 3.4 Rainfall-Based Fertilizer Decision Rule

Rainfall Condition	System Action	Reference
> 8 mm/day	Do not allow fertilizer recommendation	[3]
> 12.7 mm/week	Delay fertilizer recommendation	[1]
Moderate/Low rainfall	Show recommended NPK	[2]

E. *Web-Enabled Advisory Interface*

Once the system completes both prediction and rainfall checks, it displays either the NPK values or a warning on a web interface. Cloud-based advisory services make farming decisions more accessible without requiring soil tests, expensive field sensors or manual interpretation [16]. Similar to modern mobile and IoT-driven fertilizer advisory systems, FertiCast delivers simple and location-aware decisions digitally instead of generic fertilizer charts [13].

IV. CONCLUTION

This research demonstrates that fertilizer recommendation should not be treated as a fixed guideline but must adapt to weather fluctuations, especially rainfall, which has a direct impact on nutrient retention and crop response. Continuous studies show that nutrient losses intensify during heavy or prolonged precipitation, leading to reduced fertilizer efficiency and unnecessary cost to farmers [1], [3]. Such conditions, if ignored, lead to wastage of nitrogen and potassium due to leaching and runoff, affecting both yield and soil health.

FertiCast addresses this challenge by combining ensemble machine learning with climate-responsive advisory logic. The use of Random Forest improves prediction stability and makes nutrient estimation more reliable under varying field conditions [8], [17], [21]. This ensures that fertilizer values are not only crop-specific but also location-dependent and sensitive to climatic variations. By preventing fertilizer application during unsafe rainfall periods, the system improves nutrient use efficiency and reduces environmental losses.

Digital platforms and cloud-based advisory systems also prove beneficial in disseminating such intelligent agricultural decision support without requiring expensive laboratory testing or sensor-based infrastructure [13], [16]. As a result, FertiCast acts as a practical and accessible tool that supports real-time nutrient planning, sustainable fertilizer use, and informed agricultural decision-making.

Overall, the integration of rainfall forecasting, machine learning prediction and web-based advisory converts FertiCast into a proactive decision system rather than a static calculator. It not only suggests how much fertilizer to use but also determines when it is economically and environmentally appropriate to apply it, promoting efficient and climate-aware fertilizer management in modern agriculture.

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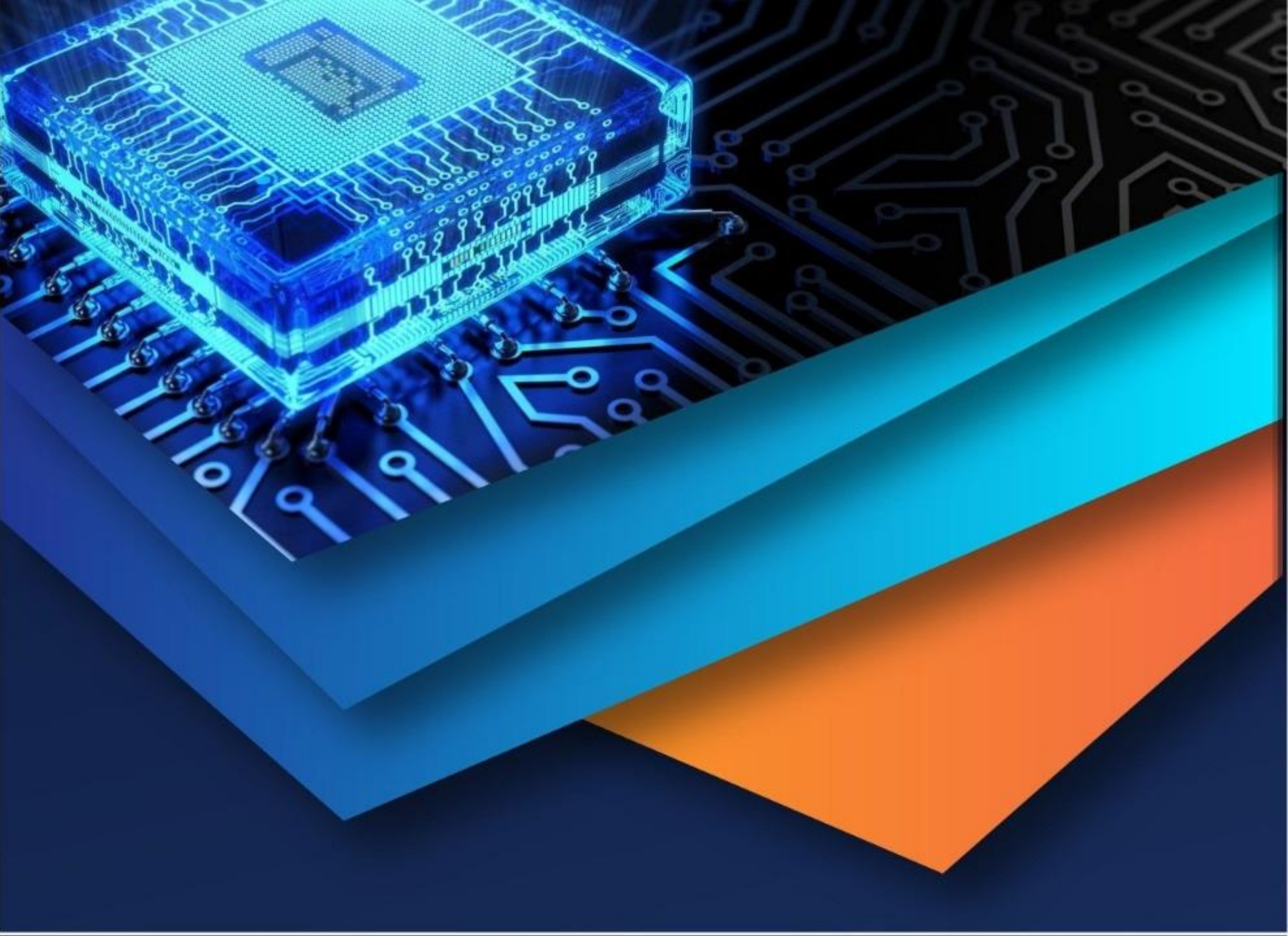

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