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Original Paper : Comparative Research – Methodology Research Paper

Precision Agriculture: AI based Fertilizer Recommendations For Sustainable Crop Production

Peddinti Neeraja [1] , Ch. Sandhyarani [2]

Department of Computer Application (MCA), Mohan Babu University, Tirupati, Andhra Pradesh, India;
neeraja.ayyangar@gmail.com , cheeraboyinasandhyarani@gmail.com

* *Corresponding Author: P. Neeraja; neeraja.ayyangar@gmail.com*

Abstract: The use of precision farming has become a transformative approach to optimizing crop production while ensuring environmental sustainability. Fertilizer application, a critical factor in agricultural productivity, is often performed using conventional methods that lead to inefficient resource utilization, soil degradation, and environmental pollution. This paper presents an AI-based fertilizer recommendation system that leverages machine learning algorithms, remote sensing data, and soil health parameters to provide precise nutrient recommendations tailored to specific crops and field conditions. The proposed model integrates data from soil sensors, weather forecasts, and historical yield patterns to generate accurate fertilizer prescriptions, reducing excess usage and enhancing crop yields. By employing AI-driven predictive analytics, the system optimizes nutrient distribution, minimizes environmental impact, and supports sustainable farming practices. Experimental results demonstrate the effectiveness of the model in improving fertilizer, efficiency while maintaining soil health and maximizing agricultural productivity. This research highlights the potential of AI in precision agriculture and provides insights into how intelligent decision-making systems can contribute to sustainable food production will focus on expanding the datasets, refining predictive models, and integrating real-time monitoring for enhanced accuracy and adaptability.

Keywords: Precision Agriculture, Fertilizer Recommendation, Machine Learning, Sustainable Farming, Soil Health.

1. Introduction

Agriculture is the backbone of global food security, yet traditional farming practices often rely on generalized fertilizer applications, leading to inefficiencies, soil degradation, and environmental pollution.

Precision agriculture, driven by advancements in artificial intelligence (AI), offers a data-driven approach to optimize fertilizer usage, enhance crop yields, and promote sustainability.AI-powered fertilizer recommendation systems leverage machine learning algorithms, remote sensing, and soil health data to provide tailored nutrient prescriptions for specific crops and soil conditions.

By analyzing various parameters such as soil composition, weather patterns, and historical yield data, these systems enable farmers to make informed decisions that minimize resource wastage and maximize productivity. This paper presents an AI-based fertilizer recommendation model designed to support sustainable crop production.

2. Literature Survey

Precision agriculture uses technology to make farming more efficient and sustainable. One important part of this is managing fertilizer use. AI and machine learning (ML) can help by recommending the right fertilizer for different crops based on things like soil, weather, and crop type. This survey looks at how different machine learning techniques, especially Random Forest (RF), have been used for fertilizer recommendations [1].

2.1. Precision Agriculture and Fertilizer Use

Traditionally, fertilizers are applied without considering exact needs, often leading to overuse or waste. Precision agriculture helps by providing the right amount of fertilizer at the right time [2]. This reduces waste and improves crop production. Studies show that using technology to manage fertilizer use can be more efficient and better for the environment [3].

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2.2. Machine Learning for Fertilizer Recommendations

Several machine learning methods are used to recommend fertilizers:

Random Forest (RF): RF is a decision tree- based model that is commonly used to predict the best fertilizer based on data like soil type, crop needs, and weather. It is effective because it can handle complex data and still make accurate predictions [4].

Other ML Algorithms: Other methods, like Artificial Neural Networks (ANNs) and Support Vector Machines (SVM) have also been used but often need more data and computational power than RF.

Random Forest in Agriculture RF is very useful in agriculture for predicting fertilizer needs

Feature Importance: RF also helps identify which factors, like soil nutrients or rainfall, are most important when deciding fertilizer amounts.

Combining with Other Models: Some studies combine RF with other techniques like K- Nearest Neighbours (KNN) to improve predictions, especially for specific crops like maize.

2.3. Challenges

Despite the benefits, there are challenges in using AI for fertilizer recommendations:

Data Quality: The models need good- quality data, such as soil tests and weather information. Sometimes, this data is not available or is of low quality [5].

Understanding Predictions: RF is a "black box" model, meaning it can be hard to understand why it makes certain recommendations, which can be a problem in farming where understanding the reasoning is important.

Real-Time Data: To make recommendations more accurate, the models need to work with real-time data, such as current soil conditions and weather. This can be difficult to implement in areas without advanced technology [6].

Future Directions: There are ways to improve AI-based fertilizer recommendations: Using Real-Time Data: By integrating real- time data from sensors and weather stations, the model can provide more accurate recommendations. Improving with Hybrid Models: Combining Random Forest with other machine learning methods could make the predictions even more accurate.

Sustainability: AI systems should aim to reduce environmental impact by promoting efficient fertilizer use and protecting soil health [7].

3. Methodology

Soil Data: Gather soil samples from various locations within your target area.

Analyze these samples for key properties: Nutrient levels (Nitrogen, Phosphorus, Potassium, etc.)pH level Organic matter content.

3.1. Moisture Levels

Crop Data: Collect data on the types of crops being grown, their growth stages, and any observed health issues.

Environmental Data: Record weather patterns, temperature, rainfall, and other relevant environmental factors.

3.2. AI Model Development

Choose an Algorithm: Select a suitable machine learning algorithm for your project. Popular Options include Random Forest, which excels at managing intricate relationships and big datasets [8].

Support Vector Machines (SVM): Good for problems involving regression and classification.

Neural Networks: Can model highly non-linear relationships.

Train the Model: Feed the collected data into your chosen algorithm to train it. The model will learn to identify patterns and correlations between soil properties, crop needs, and environmental factors.

3.3. Fertilizer Recommendation System

Input Interface: Create a user-friendly interface where farmers can input information about their fields (soil test results, crop type, etc.).AI Integration: Connect your trained AI model to the system. When a farmer provides input, the model will analyze the data and generate tailored fertilizer recommendations [9].

Output: The system will provide specific recommendations on:

Type of fertilizer to use Optimal amount of fertilizer the system. When a farmer provides input, the model will analyze the data and generate tailored fertilizer recommendations.

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Output: The system will provide specific recommendations on. Type of fertilizer to use Optimal amount of fertilizer Best time for application Validation and Refinement:

Field Trials: Conduct field trials to test the accuracy and effectiveness of your AI-based recommendations.

Gather Feedback: Collect feedback from farmers who use the system.

Refine the Model: Based on the results and feedback, make necessary adjustments to your AI model and recommendation system to improve accuracy and usability [10].

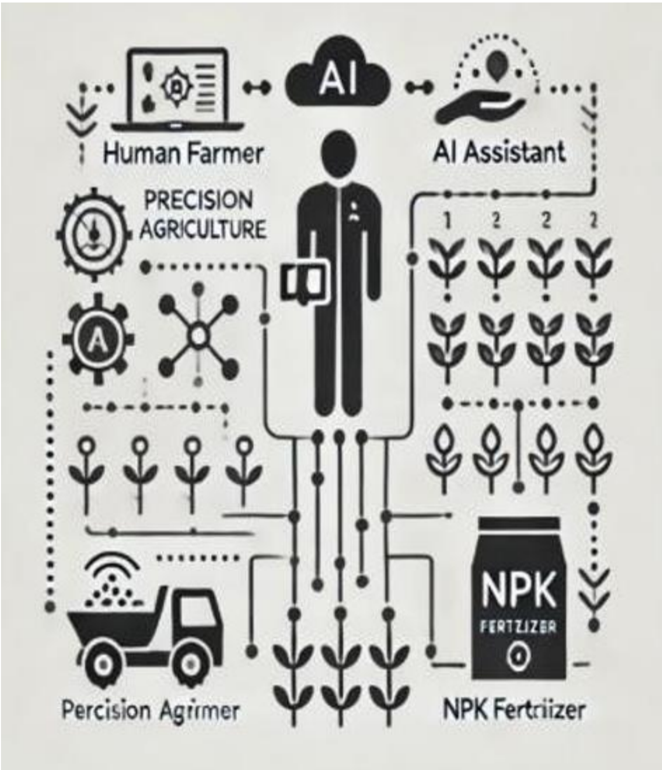

Figure.1 Sustainable Flow Mechanism

Random Forest Algorithm for Fertilizer Recommendations: The Random Forest algorithm, a robust ensemble learning technique, is employed to predict optimal fertilizer recommendations based on various input features. The algorithm constructs multiple decision trees during training and outputs the most frequent prediction (for classification tasks) or the average prediction (for regression tasks). In the context of precision agriculture, it is particularly suited for handling complex and high-dimensional datasets, which include diverse variables such as soil conditions, weather data, crop type, and growth stages [11].

Data Input: The algorithm utilizes the following data inputs: Soil Properties: Nitrogen (N), Phosphorus (P), Potassium (K), organic matter, pH levels, etc.

Weather Conditions: Temperature, rainfall, humidity, solar radiation, wind speed.

Crop Information: Crop species (e.g., maize, wheat), growth stage (e.g., germination, flowering).

Geographical and Environmental Factors: Field location, past fertilizer usage patterns, irrigation

3.4. Advantages of Using Random Forest for Fertilizer Recommendation

High Accuracy: Effectively captures non- linear relationships in agricultural data.

Robustness: Less prone to overfitting compared to traditional decision trees.

Feature Importance Analysis: Identifies critical soil and weather factors affecting fertilizer needs.

Scalability: Can be applied to large-scale agricultural datasets.

3.5. Challenges & Future Scope

Data Availability: Ensuring high-quality real- time data collection remains a challenge.
Integration with IoT & Remote Sensing: Combining machine learning with IoT-based soil sensors and satellite imagery can enhance precision.

3.6. Model Training

Creating Decision Trees: Bootstrapping, or sampling with replacement, is used to train each decision tree on a random subset of the data. At to maintain diversity in the trees, a random subset of features is taken into account for each split [12].

Ensemble Learning: Random Forest's ensemble structure guarantees that the final forecast is produced by combining the results from all separate trees, enhancing prediction accuracy and lowering the possibility of overfitting.

Prediction Output: Fertilizer Type (Classification Task): Based on the decision trees, the model predicts the most suitable type of fertilizer (e.g., Urea, DAP, MOP) for a given crop field.

Application Rate (Regression Task): The model also predicts the required application rate for the recommended fertilizer, expressed in terms of weight

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per unit area (e.g.kg/hectar)

Feature Importance: Random Forest provides an inherent mechanism for determining feature importance, which is crucial for AI-based fertilizer recommendations in precision agriculture. This is achieved through methods such as Gini impurity, mean decrease in accuracy, and permutation importance [13].

The Gini impurity-based method evaluates how well a feature splits the data, with features that reduce impurity the most being considered highly important. Meanwhile, mean decrease in accuracy assesses feature importance by randomly permuting feature values and measuring the subsequent drop in model accuracy.

Additionally, SHAP (SHapley Additive exPlanations) values offer deeper insights by assigning importance scores to each feature for individual predictions, enhancing explainability.

3.7. Key features:

Identified as highly influential in in fertilizer recommendations include soil nitrogen levels, phosphorus and potassium concentrations, rainfall patterns, and soil pH, as they directly impact plant nutrient uptake. Other moderately important factors include organic matter content, temperature, humidity, and soil moisture, which affect fertilizer efficiency and soil health [14].

Less critical but still relevant variables include soil texture, previous fertilizer applications, and data from remote sensing, like the Normalized Difference Vegetation Index (NDVI) index), which aid in further honing suggestions.

Understanding feature importance in fertilizer prediction models is essential for optimizing nutrient application, improving agricultural sustainability, and enhancing decision-making. By focusing on the most impactful features, farmers can reduce over-fertilization, minimize environmental damage, and improve crop yields. Implementing feature importance analysis in AI-driven models ensures that precision agriculture remains data-driven, efficient, and environmentally responsible.

Model Evaluation: The Random Forest model is evaluated using different metrics to check its accuracy and reliability. If the model is classifying fertilizer types, accuracy is used to measure how often it correctly predicts the right fertilizer. If the model is predicting exact fertilizer amounts, Mean Squared Error (MSE) is used to calculate how far the predicted values are from the actual application rates, with lower values indicating better performance [15].

To ensure the By using cross-validation, the model is able to generate accurate predictions on fresh data in addition to simply remembering the training set. This to avoid overfitting and enhance generalization, the method divides the data into several portions and trains and tests the model on each section.

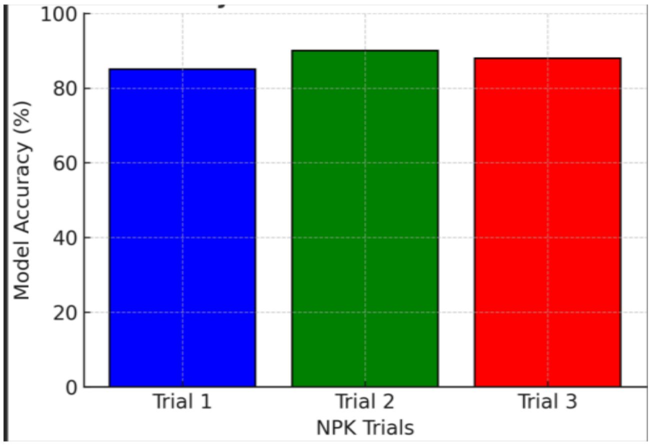

Figure.2 Data Analysis view

3.8. Advantages of Random Forest in Fertilizer Recommendation

Handles Missing Data Well – In farming, data can sometimes be incomplete due to sensor failures or missing soil test results. Random Forest can still make accurate predictions even if some data points are missing [16].

Prevents Overfitting – Unlike traditional decision trees, Random Forest reduces the risk of overfitting by using multiple trees. This ensures that the model generalizes well and provides reliable recommendations for different soil and climate conditions.

Works with Different Types of Data – Random Forest can handle both numerical data (e.g., soil pH, rainfall) and categorical data (e.g., crop type, soil category). This flexibility makes it suitable for complex agricultural datasets.

Fast and Efficient – Even with large datasets, Random Forest can quickly analyze data and generate fertilizer recommendations, making it useful for real-time decision-making in farming.

Adaptable to Different Regions – Since it learns from historical data, the model can be trained on region-specific soil and climate conditions, ensuring that fertilizer recommendations are suitable for different farming areas

Reliable in Changing Conditions – Agriculture is affected by weather changes, soil variations, and new farming practices. Random Forest's ability to analyze multiple factors at once helps it provide stable

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and reliable fertilizer recommendations even when conditions change.

3.9. Dataset Description for AI-Based Fertilizer Recommendations

The dataset includes detailed information about soil, crops, weather, fertilizer use, and environmental factors to help the AI model recommend the best fertilizer. Below are the key components:

Soil Information:
Soil Type – Identifies the soil category (e.g., sandy, clay, loamy).

Soil pH – Measures soil acidity or alkalinity, affecting nutrient availability.

Soil Nutrients (N, P, K) – Indicates levels of nitrogen (N), phosphorus (P), and potassium (K), which are essential for plant growth.

Soil Moisture (%) – Determines how much water is present in the soil.

3.10. Crop Information

Crop Type – Specifies the crop being grown (e.g., wheat, maize, rice).

Growth Stage – Indicates whether the

3.10.1. Fertilizer Details

Fertilizer Type – Specifies the type of fertilizer used (e.g., nitrogen-based, organic, phosphorus-rich).

Fertilizer Quantity (kg/ha) – Records the amount of fertilizer applied per hectare.

Application Method – Describes how the fertilizer was applied (e.g., broadcasting, drip

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3.10.2. Weather Data

Temperature (°C) – Measures the average temperature during crop growth.

Rainfall (mm/month) – Tracks the amount of precipitation, affecting soil moisture and nutrient absorption.

Solar Radiation (W/m²) – Indicates the amount of sunlight received, influencing photosynthesis.

Humidity (%) – Shows the moisture content in the air, which affects plant transpiration.

3.10.3. Location & Environmental Factors

Location – Provides geographical coordinates or regional classification.

Land Slope (%) – Determines how steep the land is, affecting water and fertilizer absorption.

Soil Erosion Risk – Assesses if the area is prone to losing soil due to wind or water erosion.

3.10.4. Fertilizer Recommendation (Target Variable)

Recommended Fertilizer Type – Suggests the best fertilizer based on soil and crop conditions.

4. Conclusion and Future Scope

In this paper, we demonstrated how the Random Forest algorithm can be used to provide AI-based fertilizer recommendations for precision agriculture. By analyzing various factors like soil conditions, weather, and crop type, the model can recommend the right fertilizer type and application rate to improve crop yield while being environmentally friendly. The results show that Random Forest is a reliable method for making accurate fertilizer predictions. It is especially useful because it can handle large, noisy datasets and provide insights into which factors are most important for fertilizer decisions. Overall, this approach offers a practical solution for farmers to use fertilizers more efficiently, helping to reduce waste and improve crop production. While there are still some challenges, like the need for real- time data, the system shows great potential for improving agricultural practices and promoting sustainability. Future work will focus on improving the model's performance, integrating real- time data, and exploring other AI methods to make it even more effective.

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Table.4 Hotels

Hotel	Location	Country	Region	Company	Score	Rank	Rooms	Theme	Year
Mahali Mzuri	Masai Mara	Kenya	Africa	Virgin Limited Edition	99.73	1	12	Safari	2013
Nayara Tented Group	Arenal Volcano National Park	Costa Rica	Latin America	Nayara Resorts	99.58	2	29	Nature	2019
The Opposite House	Beijing	China	Asia	Swire Properties	99.47	3	99	Contemporary	2009
Capella Bangkok	Bangkok	Thailand	Southeast Asia	Pontiac Land Group	99.38	4	101	Contemporary	2020
Capella Ubud	Bali	Indonesia	Southeast Asia	Pontiac Land Group	99.34	5	23	Nature	2018
Grace Hotel	Santorini	Greece	Europe	Auberge Resorts Collection	99.18	6	139	Coastal	2008
Kamalame Cay	Andros Island	Bahamas	Caribbean	David and Michael King-Hew	99.14	7	22	Island	1996
The Oberoi Udaivilas	Udaipur	India	Southeast Asia	The Oberoi Group	99.12	8	87	Palace	2007
The Temple House	Chengdu	China	Asia	Swire Properties	98.94	9	142	Contemporary	2003