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Web-Based Fertilizer Recommendation System Using Soil, Crop, And Environmental Parameters With Random Forest Classifier

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Abstract: The agricultural sector plays a crucial role in food security where crop productivity is highly dependent on the availability of nutrients in the soil such as Nitrogen (N), Phosphorus (P), and Potassium (K). However, inappropriate fertilization practices, whether insufficient or excessive, can damage soil structure and reduce crop yields. Farmers often have difficulty in precisely determining the most appropriate type of fertilizer based on specific soil and weather conditions. This study aims to build an intelligent recommendation system based on Machine Learning that can accurately predict fertilizer types. The algorithm used in this classification is the Random Forest Classifier which was chosen because of its ability to handle complex data sets and minimize overfitting. The software development method applied is the Agile method which allows for an iterative development process and is responsive to changing needs. The parameters used as input values include temperature, air humidity, soil moisture, soil color, plant type, and N, P, and K levels. The results of model testing using evaluation measurements show that the Random Forest algorithm is able to provide an accuracy level of 91.25% in predicting the right fertilizer class for various types of agricultural crops. This system can help farmers make more efficient and data-driven fertilization decisions.

Keywords: Agile, Machine Learning, Agriculture, Random Forest Classifier, Fertilizer Recommendation

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1 Introduction

The agricultural sector plays a crucial role in maintaining stable food security. Crop productivity in this sector is highly dependent on soil quality and adequate nutrient availability. Macronutrients such as nitrogen (N), phosphorus (P), and potassium (K) are fundamental components that determine the growth rate of various agricultural commodities, from staple food crops like rice and wheat to commercial crops like sugarcane and cotton [1]. However, agricultural land conditions are highly heterogeneous and are constantly influenced by environmental factors such as soil acidity (pH), rainfall, and air temperature [2].

To date, many farmers still rely on intuition or inherited habits to determine the type of fertilizer to apply to their land. Fertilization that is not based on precise calculations of agronomic data often results in inappropriate nutrient delivery. Excessive fertilizer use not only leads to financial waste but also risks environmental pollution and long-term soil fertility degradation. Conversely, fertilization that falls below the required threshold will result in suboptimal plant growth or even crop failure.

Given the numerous variables that must be evaluated simultaneously, including N, P, and K levels, soil pH, soil color, rainfall, temperature, and even the target crop species, a computational analytical instrument capable of processing these data patterns quickly and accurately is required. The application of Machine Learning technology offers a highly effective solution for solving this multivariable classification problem [3]. Among the various available algorithms, the Random Forest Classifier was specifically selected for this study. This algorithm is an ensemble method proven to be robust in processing tabular data with many attributes, capable of automatic feature selection, and highly reliable in minimizing bias (overfitting), a common weakness of single conventional classification models [4].

To ensure that this artificial intelligence prediction system does not remain merely an experimental model, this study also integrates Machine Learning into a web-based system interface using the Laravel framework [5]. The use of this architecture allows the analytical model on the backend to be easily accessed by end users (farmers or agricultural extension workers) through a responsive and interactive interface.

The existing literature has demonstrated that machine learning techniques, particularly the Random Forest algorithm, can achieve high prediction accuracy for crop and fertilizer recommendation tasks [6]. However, most previous studies primarily emphasize algorithmic performance evaluation and are often limited to offline experiments using public datasets.

Comparatively fewer studies have focused on translating these predictive models into deployable decision-support systems that can be directly utilized by farmers in practical agricultural environments. In addition, limited attention has been given to integrating fertilizer recommendation with interactive web-based platforms, usability evaluation involving end users, and interpretation of model decisions through feature importance analysis. These gaps limit the practical applicability and transparency of existing machine learning-based fertilizer recommendation systems.

In its development process, this research applied Agile methodology to accommodate the experimental nature of Machine Learning modeling, which requires repeated iterations between data processing, algorithm adjustments, and result evaluation [7]. Therefore, this study aims to develop, implement, and evaluate a web-based intelligent fertilizer recommendation system using the Random Forest Classifier by integrating soil nutrients, crop characteristics, and environmental parameters into a practical decision-support platform for precision agriculture. The results of this intelligent system are expected to provide practical benefits as a data-driven precision tool for farmers, while also enriching the literature on the application of artificial intelligence technology in the smart agriculture sector [8].

Based on the identified research gap, the main contributions of this research are summarized as follows:

(1) Developing a complete web-based fertilizer recommendation system that integrates a Random Forest prediction model with a Laravel-based decision-support platform.

(2) Integrating soil nutrient parameters, crop characteristics, and environmental variables into a unified fertilizer recommendation framework.

(3) Deploying the prediction model through an API to provide real-time fertilizer recommendations.

(4) Evaluating the practical usability of the developed system through User Acceptance Testing (UAT) involving farmers.

(5) Interpreting feature importance to identify influential agronomic variables and improve the transparency of the prediction model.

2 Related Work

Previous studies have increasingly explored the integration of machine learning in smart farming to address multivariable agricultural challenges. For instance, [1] highlighted the effectiveness of machine learning approaches in estimating nitrogen status and predicting crop yield by analyzing environmental and soil factors. Similarly, [9] developed recommendation models for agricultural crops based on NPK, soil pH, and climatic variables, proving that data-driven models significantly outperform traditional farming heuristics. Not only that, [6] successfully applied Random Forest and hierarchical clustering models to historical datasets specifically to provide crop and fertilizer recommendations. Building upon these existing foundations, this research not only optimizes a Random Forest Classifier for fertilizer prediction but also bridges the gap between theoretical modeling and practical application by developing an Agile-based, interactive web platform (AgriSmart) for real-time farmer use.

3 Methods

3.1 Research Design

This research aims to develop a fertilizer recommendation software system powered by artificial intelligence [9]. In the overall system design and development, this research adopted the Agile software development methodology.

The Agile methodology was chosen because it accommodates iterative system development and is responsive to change, both in terms of adjusting the Machine Learning model and adjusting the web system interface [10]. In accordance with the Agile framework, the development cycle in this research is outlined in seven stages, as shown in Figure 1.

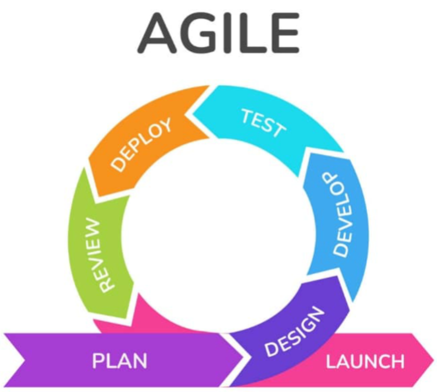

Figure 1. Overall Workflow of AI-Based Fertilizer Recommendation System.

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3.2 System Workflow

A research flowchart is used to systematically illustrate the research stages, from problem identification to system evaluation. This diagram, as shown in Figure 2, aims to facilitate understanding of the development flow of the Random Forest Classifier-based fertilizer recommendation system used in this study.

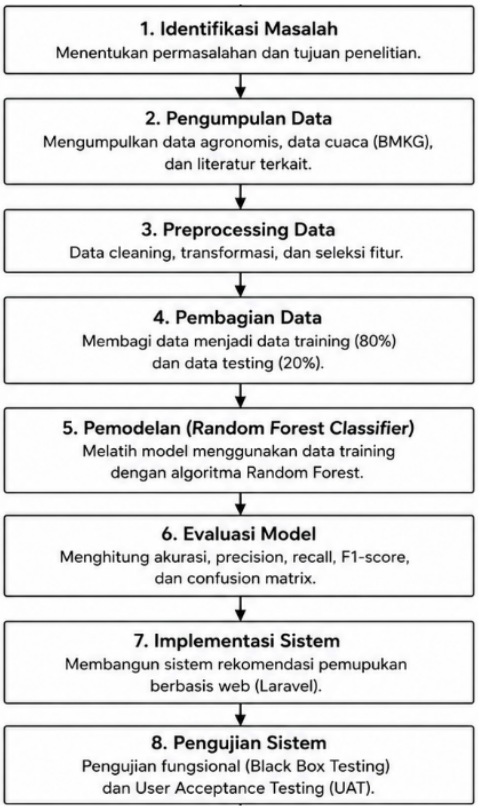

Figure 2. Research Workflow

3.3 Data Collection and Preprocessing

The dataset used in this study is the Crop and Fertilizer Dataset for Western Maharashtra, which is publicly available through the Kaggle repository. The dataset contains 4,513 historical agronomic records collected from agricultural observations in the Western Maharashtra region of India. It was published for research and educational purposes and includes information describing soil characteristics, environmental conditions, crop types, and corresponding fertilizer recommendations. The dataset is publicly accessible through Kaggle under its dataset-sharing policy.

Eight relevant input features were selected for this study, namely soil color, Nitrogen (N), Phosphorus (P), Potassium (K), soil pH, rainfall, temperature, and crop type. The target variable consists of 19 fertilizer classes. These variables represent the major agronomic and environmental factors that influence fertilizer selection.

The preprocessing stage was conducted to improve data quality and optimize the performance of the Machine Learning model. Initially, irrelevant attributes such as Link and District_Name were removed because they did not contribute to the fertilizer classification process. The dataset was then examined for missing values and duplicate records to ensure data consistency and integrity. Experimental analysis confirmed that the dataset contained no missing values and no duplicated entries. Several categorical attributes, including soil color, crop type, and fertilizer class, were transformed into numerical representations using the Label Encoding technique. This transformation enabled the Random Forest Classifier to process categorical information efficiently.

After preprocessing, the dataset consisted of 4,513 records with eight input features and one target variable. The dataset was divided into 80% training data (3,610 samples) and 20% testing data (903 samples) using stratified sampling to preserve class distribution balance [11]. Finally, numerical features were standardized using the StandardScaler method to normalize feature scales and improve model stability during training. The overall preprocessing workflow is illustrated in Figure 3.

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```
[2a] Drop kolom 'Link' dan 'District_Name' (jika ada) → shape: (4513, 9)
[2b] Missing values per kolom:
Soil_color     0
Nitrogen       0
Phosphorus     0
Potassium      0
pH             0
Rainfall       0
Temperature    0
Crop           0
Fertilizer     0
dtype: int64
→ Tidak ada missing values ✓
[2c] Jumlah duplikat: 0
→ Tidak ada duplikat ✓
[2d] Label Encoding kolom kategorikal:
Soil_color     → 7 kelas unik
Crop           → 16 kelas unik
Fertilizer     → 19 kelas unik (target)

Kelas Fertilizer: ['10:10:10 NPK', '10:26:26 NPK', '12:32:16 NPK', '13:32:26 NPK', '18:46:00 NPK',
'19:19:19 NPK', '20:20:20 NPK', '50:26:26 NPK', 'Ammonium Sulphate', 'Chelated Micronutrient',
'DAP', 'Ferrous Sulphate', 'Hydrated Lime', 'MOP', 'Magnesium Sulphate', 'SSP', 'Sulphur', 'Urea',
'White Potash']
[2e] Pisah fitur (X) dan target (y):
X shape : (4513, 8)
y shape : (4513,)
Fitur   : ['Soil_color', 'Nitrogen', 'Phosphorus', Kalium', 'pH', 'Rainfall', 'Temperature', 'Crop']
[2f] Train-Test Split (80:20, stratified):
Train : 3610 sampel
Test  : 903 sampel
```

Figure 3. Preprocessing

3.4 Random Forest Classification Model

The Random Forest Classifier was utilized to predict the required fertilizer. The algorithm builds multiple decision trees using bootstrap aggregation (bagging) on the training data. The final classification result is obtained through a majority vote from all generated decision trees, mathematically expressed as:

$$\hat{y} = mode\{h_1(x), h_2(x), \dots, h_n(x)\} \tag{1}$$

Where $\hat{y}$ is the final predicted output, x is the input parameter set, $h_i(x)$ is the prediction of an individual decision tree, and n is the total number of trees, and mode() selects the class with the highest voting frequency.

The Random Forest model was implemented using the Scikit-learn library. The classifier was configured with 200 decision trees (n_estimators = 200), unlimited tree depth (max_depth = None), balanced class weights (class_weight = "balanced"), a fixed random seed (random_state = 42) to ensure reproducibility, and parallel processing across all available CPU cores (n_jobs = -1) to improve computational efficiency. These hyperparameter values were selected based on empirical implementation considerations. No systematic hyperparameter tuning, such as Grid Search or Random Search, was performed in this study. Therefore, the reported performance reflects the effectiveness of the proposed system using a manually configured Random Forest model.

3.5 System Implementation

The proposed fertilizer recommendation system was implemented as a web-based application named AgriSmart. The frontend interface was developed using the Laravel framework to provide an interactive and user-friendly environment for farmers and agricultural users [12]. The Machine Learning prediction model was developed separately using Python and integrated into the web application through an Application Programming Interface (API). This integration allows real-time communication between the Laravel-based frontend and the Random Forest prediction engine [13].

Users are required to input several agricultural parameters, including Nitrogen (N), Phosphorus (P), Potassium (K), soil pH, rainfall, temperature, soil color, and crop type. To ensure accurate input parameters, users can measure the levels of N, P, K, and soil acidity (pH) in real time using a portable Soil Test Kit or integrate readings from an Internet of Things (IoT) based soil quality sensor [14]. Meanwhile, for climate parameters such as rainfall and temperature, users can refer to the Meteorology, Climatology, and Geophysics Agency (BMKG) database or the nearest weather station. To facilitate the input process, the system also provides a geolocation detection feature to automatically retrieve temperature data based on the user's location when accessing the site.

After the input data is submitted, the system sends the parameters to the backend API, where the Random Forest Classifier processes the data and generates fertilizer recommendations. The prediction results are then returned to the web application and displayed to users in real time. In addition, the system provides features for recommendation visualization, result history management, and printable recommendation reports to support practical agricultural decision-making. The implementation interface of the proposed web-based fertilizer recommendation system is presented in Figure 5.

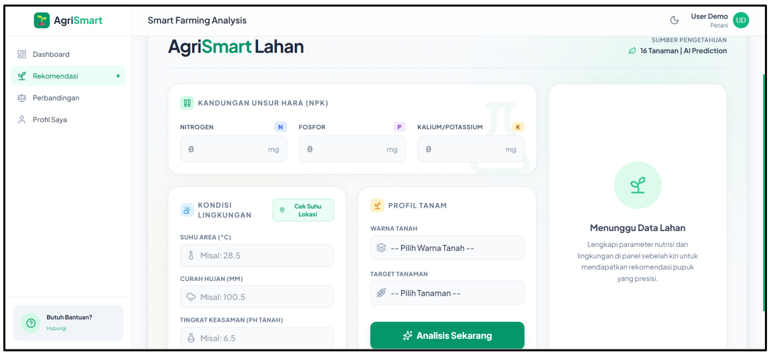

Figure 4. Web-Based Fertilizer Recommendation Interface

3.6 Evaluation Metrics

The model's performance on the 20% test set was evaluated using a Confusion Matrix to calculate Accuracy, Precision, Recall, and the F1-Score. Furthermore, Black-box testing and User Acceptance Testing (UAT) were employed to evaluate the functional reliability and user satisfaction of the final web application.

The accuracy formula is defined as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

The precision formula is defined as:

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

The recall formula is defined as:

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

The F1-Score formula is defined as:

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{5}$$

4 Results and Discussion

4.1 Experimental Findings and Model Performance

The experimental evaluation was conducted using 20% of the dataset as testing data, consisting of 903 samples that were not involved during the training phase. The Random Forest Classifier demonstrated strong classification performance in predicting fertilizer categories based on soil nutrients, environmental conditions, and crop characteristics.

Experimental results showed that the proposed model achieved an overall accuracy of 91.25%, indicating that the classifier successfully learned the complex relationships between agricultural parameters and fertilizer requirements. The weighted average Precision reached 0.92, while both Recall and F1-Score achieved 0.91, demonstrating stable and balanced classification performance across multiple fertilizer classes. The overall performance evaluation results of the proposed model are presented in Table 1.

Table 1: Performance Evaluation of the Random Forest Classifier

Model	Accuracy	Precision	Recall	F1-Score
Random Forest Classifier	91.25%	0.92	0.91	0.91

The model performed particularly well on dominant fertilizer categories such as Urea, DAP, and MOP, each obtaining F1-Scores above 0.90. These results indicate that the Random Forest algorithm effectively handled multidimensional agricultural data and minimized overfitting during the training process.

However, several minority fertilizer classes exhibited lower precision values due to limited sample distribution within the dataset. This imbalance slightly affected classification consistency for rare fertilizer categories. Nevertheless, the overall weighted evaluation metrics remained highly stable, confirming the robustness and generalization capability of the proposed recommendation model for practical smart agriculture applications. Detailed classification results for major fertilizer categories are shown in Table 2.

Table 2. Classification Performance for Major Fertilizer Classes

Fertilizer Class	Precision	Recall	F1-Score	Support
Urea	0.91	0.90	0.91	273
DAP	0.95	0.93	0.94	134
MOP	0.95	0.91	0.93	114
SSP	0.86	0.80	0.82	83
Magnesium Sulphate	1.00	0.95	0.98	43

4.2 Confusion Matrix Analysis

To further evaluate the classification capability of the proposed model, a Confusion Matrix was generated to compare the predicted fertilizer classes against the actual labels from the testing dataset. The Confusion Matrix provides a detailed visualization of correct and incorrect classifications across all fertilizer categories.

The diagonal values in the matrix represent correctly classified instances, while the off-diagonal values indicate misclassification errors between fertilizer classes. Based on the experimental results, the Random Forest Classifier demonstrated strong predictive consistency for dominant fertilizer categories such as Urea, DAP, and MOP, where most predictions were concentrated along the main diagonal, as illustrated in Figure 5.

Minor misclassifications mainly occurred among fertilizer classes with limited training samples or similar nutrient compositions. Nevertheless, the overall distribution confirms that the proposed model possesses strong discriminative capability and reliable generalization performance for agricultural fertilizer recommendation tasks. The confusion matrix also confirms that the model maintains stable prediction behavior across both majority and minority fertilizer categories.

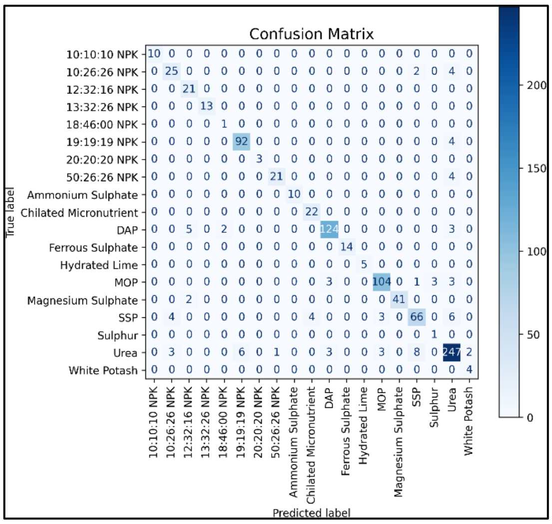

Figure 5. Confusion Matrix of the Random Forest Classifier

4.3 Feature Importance Analysis

One of the advantages of the Random Forest algorithm is its ability to measure the significance level of each input parameter on the prediction results [4]. Based on Figure 6, Potassium is the most dominant feature with an importance value of 0.206, followed by the type of plant or Crop (0.176) and Phosphorus (0.170). The high weights of Potassium and

Phosphorus indicate that variations in macronutrient levels in the soil are the most critical determinants for the model in distinguishing fertilizer classes. In addition, the Crop parameter ranks second highest because each type of agricultural commodity has a very specific nutrient absorption profile. Conversely, Soil_color (0.052) has the lowest importance level, which confirms that the visual characteristics of the soil do not have a significant classification impact compared to the chemical composition of the soil itself.

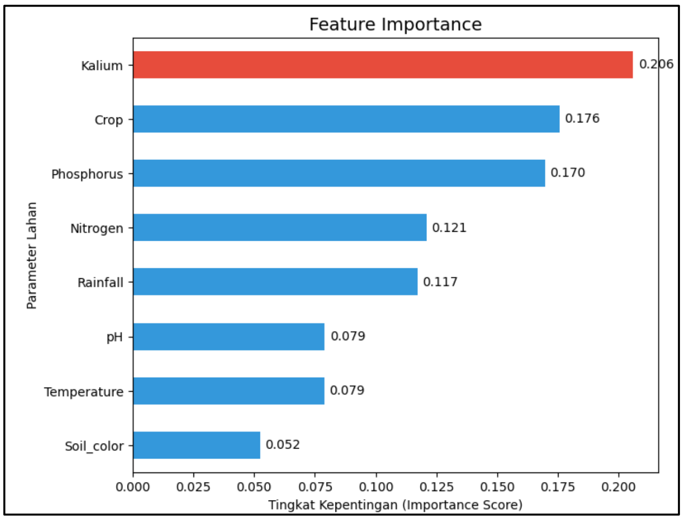

Figure 6. Feature Importance of the Random Forest Classifier

4.4 System Implementation and Testing

4.4.1 Black-box Testing

Black box testing was conducted to verify that each function in the AI-based fertilizer recommendation system operates according to user requirements. Tested features included user login, plant data input, the AI-based fertilizer recommendation process, fertilizer comparison, fertilizer data management by the administrator, and other supporting features. Test results showed that each system function operated properly and produced results as expected. Details of the test scenarios and results are presented in Table 3.

Table 3. Black-box Testing Results

No	Feature	Test Scenario	Expected Results	Results
1	Login	The user logs in with valid, invalid, or empty data	The system displays a dashboard or error message based on the conditions	Valid

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2	Plant Data Input	The user inputs plant data (plant type, soil color, etc.)	The data is successfully processed or validation appears if incomplete	Valid
3	Fertilizer Recommendation	he system processes user input to generate recommendations	The system displays fertilizer recommendation results based on the input data	Valid
4	Fertilizer Comparison	The user selects the same fertilizer	The system displays a comparison of the nutrient content of the two fertilizers	Valid
5	Fertilizer Data Management	The admin adds, changes, and deletes fertilizer data	Fertilizer data is saved, updated, or deleted correctly	Valid
6	User Management	The admin manages user data	User data is successfully added, changed, or deleted	Valid
7	Results Display	The system displays recommendation results and comparisons	Information displayed based on the processed data	Valid
8	Error Handling	The input is empty or invalid	The system displays an error message without error/crash	Valid
9	Print Report	Prints the recommendation results	The system displays a preview and can download the report	Valid
10	Logout	The user exits the system	The system returns to the main page/landing page	Valid

4.4.2 User Acceptance Testing (UAT)

User Acceptance Testing (UAT) was conducted to measure the level of end-user acceptance and satisfaction with the developed system. This testing involved 17 respondents, all farmers. The assessment used a closed-ended questionnaire based on a Likert scale with five levels: Very Good (score 5), Good (score 4), Fair (score 3), Poor (score 2), and Very Poor (score 1).

The questionnaire consisted of six main questions covering aspects of the system's ease of use, suitability of features to user needs, clarity of information, system response speed, reliability of fertilizer recommendations, and overall user satisfaction. To determine the system's suitability, a percentage index was calculated using the following formula:

$$Persentase = \frac{Total\,Skor\,Aktual}{Total\,Skor\,Maksimal} \times 100\% \tag{5}$$

Based on the questionnaire summary, the maximum total score was 510, obtained by calculating the number of respondents, the number of questions, and the highest score on the Likert scale.

$$17 \times 6 \times 5 = 510 \tag{6}$$

Meanwhile, the total actual score obtained from all respondents' answers was 424. Therefore, the user acceptance percentage is calculated as follows:

$$\frac{424}{510} \times 100\% = 83.14\% \tag{7}$$

5 Conclusion

This study successfully developed and implemented an intelligent fertilizer recommendation system using the Random Forest Classifier algorithm for smart agriculture applications. The proposed model demonstrated strong predictive capability in mapping complex relationships between soil nutrients, environmental conditions, and crop characteristics to generate accurate fertilizer recommendations.

Experimental evaluation showed that the Random Forest model achieved an accuracy of 91.25%, with stable Precision, Recall, and F1-Score values across multiple fertilizer classes. Feature importance analysis further confirmed that Potassium, crop type, and Phosphorus were the most influential parameters in the prediction process.

The integration of the Machine Learning model into a Laravel-based web application also demonstrated practical feasibility for real-world agricultural decision-support systems. User Acceptance Testing results, which achieved a satisfaction score of 83.14%, indicate that the developed system is considered useful, user-friendly, and applicable for precision agriculture practices.

Despite the promising results, this study has several limitations. First, the prediction model was developed and evaluated using a publicly available dataset collected from the Western Maharashtra region of India, which may limit its generalizability to other geographical regions with different soil and environmental characteristics. Second, although the Random Forest Classifier demonstrated satisfactory performance, this study did not perform systematic hyperparameter optimization or compare its performance with other machine learning algorithms. Finally, several environmental and agronomic factors that may influence fertilizer selection, such as soil moisture, organic matter content, and real-time sensor data, were not included in the current model. These limitations provide opportunities for future research to improve the robustness and applicability of the proposed fertilizer recommendation system.

For future work, the proposed system can be further enhanced through integration with Internet of Things (IoT) sensors for real-time soil monitoring, expansion of agricultural datasets, and comparison with advanced Machine Learning or Deep Learning algorithms to improve prediction accuracy and scalability.

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Funding Information

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Conflict of Interest Statement

The authors declare no conflicts of interest.

Ethical Approval

This study did not involve human or animal subjects.

Data Availability

The dataset used in this study is the Crop and Fertilizer Dataset for Western Maharashtra, a secondary dataset that is publicly available through the Kaggle repository. The dataset can be accessed at: https://www.kaggle.com/datasets/sanchitagholap/crop-and-fertilizer-dataset-for-westernmaharashtra. It contains historical agricultural records from the Western Maharashtra region of India and is available for research and educational purposes in accordance with Kaggle's dataset-sharing policy.

References

[1] A. Chlingaryan, S. Sukkarieh, and B. Whelan, "Machine learning approaches for crop yield prediction and nitrogen status estimation in precision agriculture: A review," *Comput. Electron. Agric.*, vol. 151, pp. 61–69, Aug. 2018, doi: 10.1016/J.COMPAG.2018.05.012.

[2] R. R. Rizqullah and M. Maryam, "Rancang Bangun Aplikasi Android untuk Rekomendasi Aktivitas Fisik berbasis Kondisi Cuaca," *Pros. Kolok. Ris. Mhs.*, Oct. 2025, Accessed: Apr. 16, 2026. [Online]. Available: https://proceedings.ums.ac.id/korma/article/view/6772

[3] Y. Paliwal and S. K. Upadhyay, "Crop and Fertilizer Recommendation System Using Machine Learning," *Proc. Int. Conf. Comput. Intell. Inf. Retrieval. ICCIIR 2025*, vol. 2, pp. 205–215, 2026, doi: 10.1007/978-3-032-04539-3_15.

[4] S. Shastri, S. Kumar, V. Mansotra, and R. Salgotra, "Advancing crop recommendation system with supervised machine learning and explainable artificial intelligence," *Sci. Reports 2025 151*, vol. 15, no. 1, pp. 25498-, Jul. 2025, doi: 10.1038/s41598-025-07003-8.

[5] D. R. Bommireddy, "Recommendation System using machine learning for fertilizer prediction," *Electron. Theses, Proj. Diss.*, May 2024, Accessed: Oct. 15, 2025. [Online]. Available: https://scholarworks.lib.csusb.edu/etd/1943

[6] S. S. Nandom, G. T. Abe, and I. P. Gambo, "Application of random forest and hierarchical clustering models for crop and fertilizer recommendation to farmers," *Niger. J. Technol.*, vol. 44, no. 1, pp. 114–122, May 2025, doi: 10.4314/NJT.V44I1.13.

[7] A. S. D. T. Haniva, J. A. Ramadhan, "Systematic Literature Review Penggunaan Metodologi Pengembangan Sistem Informasi Waterfall, Agile, dan Hybrid," *J. Inf. Eng. Educ. Technol.*, vol. 7, pp. 36–42, 2023, doi:

https://doi.org/10.26740/jieet.v7n1.p36-42.

[8] F. S. Prity *et al.*, “Enhancing Agricultural Productivity: A Machine Learning Approach to Crop Recommendations,” *Human-Centric Intell. Syst.*, vol. 4, no. 4, pp. 497–510, Dec. 2024, doi: 10.1007/S44230-024-00081-3.

[9] B. Dey, J. Ferdous, and R. Ahmed, “Machine learning based recommendation of agricultural and horticultural crop farming in India under the regime of NPK, soil pH and three climatic variables,” *Heliyon*, vol. 10, no. 3, p. e25112, Feb. 2024, doi: 10.1016/J.HELIYON.2024.E25112.

[10] S. H. Nova, A. P. Widodo, and B. Warsito, “Analisis Metode Agile pada Pengembangan Sistem Informasi Berbasis Website: Systematic Literature Review,” *Techno.Com*, vol. 21, no. 1, pp. 139–148, Feb. 2022, doi: 10.33633/TC.V21I1.5659.

[11] W. (Wiwit) Supriyanti, N. (Nur) Hasanah, and N. (Nulngafan) Nulngafan, “Machine Learning: Konsep, Algoritma, dan Implementasi,” Nov. 2025, Accessed: Apr. 11, 2026. [Online]. Available: https://repository.qrisetindonesia.com/publications/669242/

[12] T. Wisnu Noviyanto and Maryam, “Rancang Bangun Sistem Informasi Manajemen Keuangan Proyek Konstruksi menggunakan Framework Laravel,” *Pros. Kolok. Ris. Mhs.*, Oct. 2025, Accessed: Apr. 16, 2026. [Online]. Available: https://proceedings.ums.ac.id/korma/article/view/6780

[13] R. A. Pratama and D. Priyawati, “Perancangan Sistem Berbasis Website Untuk Mendukung Program Inovasi Kewirausahaan (PIK) Universitas Muhammadiyah Surakarta,” *Pros. Kolok. Ris. Mhs.*, Oct. 2025, Accessed: Apr. 16, 2026. [Online]. Available: https://proceedings.ums.ac.id/korma/article/view/6705

[14] R. Hartono, N. M. Yoeseph, F. A. Purnomo, M. A. Safi’ie, and S. A. T. Bawono, “Portable internet of things-based soil nutrients monitoring for precision and efficient smart farming,” *Bull. Electr. Eng. Informatics*, vol. 13, no. 5, pp. 3326–3333, Oct. 2024, doi: 10.11591/EEI.V13I5.7928.