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An Ensembled Crop Recommendation System Using Soil Analysis and Image Classification

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ABSTRACT

The increasing demand for intelligent agricultural decision support systems has led to the development of numerous crop recommendation models. However, most existing systems in the literature rely solely on either soil nutrient data or image-based soil classification, resulting in limited accuracy, reduced flexibility, and poor adaptability in real-world farming scenarios, especially in resource-constrained regions. Additionally, many approaches require complete and manually inputted soil parameters, which are often unavailable to smallholder farmers. To address these limitations, this study proposes a hybrid crop recommendation system that integrates both soil nutrient analysis and image-based soil classification to improve prediction reliability and usability. The system employs a Convolutional Neural Network (CNN) for soil image classification and a Logistic Regression model for crop prediction based on soil nutrient parameters, including Nitrogen (N), Phosphorus (P), Potassium (K), pH, and soil type. While advanced variants of CNN and more complex classifiers exist, the selected models were chosen due to their computational efficiency, interpretability, and suitability for deployment in low-resource environments. The CNN model classifies soil images into five categories Alluvial, Black, Clay, Red, and Sandy with an accuracy of 92.95%, while the Logistic Regression model achieves 87.40% accuracy in crop prediction. A hybrid decision framework is introduced to combine outputs from both models, allowing users to input either nutrient data, soil images, or both, thereby enhancing system flexibility. The system is implemented in Python and deployed using a Streamlit-based web interface, providing real-time and user-friendly crop recommendations. By integrating multiple data sources, the proposed approach improves decision accuracy, reduces dependency on complete data inputs, and supports sustainable agricultural practices. This study further highlights the need for extending crop recommendation systems to include fertilizer type and quantity recommendations using multidimensional agricultural data.

Keywords: Hybrid Crop Recommendation System, Soil Image Classification, Convolutional Neural Network (CNN), Logistic Regression, Precision Agriculture.

1. INTRODUCTION

The agricultural sector plays a vital role in the global economy by providing food and raw materials for various industries (Kulkarni et al., 2018). Crop productivity is highly dependent on soil characteristics, as different crops require specific nutrient compositions, moisture levels, and environmental conditions (Augusto et al., 2019). Selecting appropriate crops based on soil classification is therefore essential for maximizing yield, optimizing resource utilization, and ensuring sustainable farming practices. Traditionally, farmers rely on experiential knowledge for crop selection; however, this approach lacks scalability, precision, and efficiency. The emergence of machine learning (ML) and data-driven technologies offers new opportunities to enhance crop recommendation and fertilizer management systems (Bittar et al., 2018; Gaikwad et al., 2022).

Precision agriculture emphasizes site-specific farming practices to improve productivity and sustainability (Gosai et al., 2021). By leveraging data from weather stations, sensors, satellites, and farm equipment, ML algorithms can analyze complex agricultural parameters and provide intelligent recommendations. Such systems promote optimized usage of water, fertilizers, and pesticides, thereby reducing environmental impact while maintaining long-term agricultural viability.

Many farmers in Nigeria and other developing regions lack access to soil testing facilities and technical expertise to interpret soil data, resulting in poor soil–crop matching, low yields, resource wastage, and soil degradation (Sanjay, 2019). Existing crop recommendation systems typically require manual nutrient input, which may not be practical for small-scale farmers (Shastry & Sanjay, 2019). Conversely, image-based soil classification alone does not provide sufficient nutrient-level information for accurate crop recommendations.

Therefore, this study aims to develop an intelligent hybrid crop recommendation system that differs from existing approaches by addressing key limitations in current literature, particularly the reliance on single-source input (either soil nutrients or soil images) and the requirement for complete data availability. Unlike prior works, the proposed system introduces a flexible multi-input framework that allows farmers to provide soil nutrient data, soil images, or both, making it suitable for real-world deployment in resource-constrained environments.

Furthermore, this study incorporates a hybrid decision-making mechanism that dynamically combines predictions from both models to improve recommendation reliability, especially in cases of incomplete or uncertain data. This integrated and adaptive approach enhances robustness, reduces dependency on perfect data conditions, and provides a more practical solution compared to existing crop recommendation systems.

2. RELATED WORKS

This section reviews recent studies on soil classification and crop recommendation using machine learning and deep learning techniques for intelligent agricultural decision-making. Soil classification remains a critical component in precision agriculture due to its impact on crop productivity, land management, and environmental sustainability (Gaikwad et al., 2022; Babbe et al., 2022). Recent studies have increasingly applied machine learning algorithms such as Random Forest, Support Vector Machines (SVM), and Gradient Boosting for soil and crop prediction tasks, demonstrating improved accuracy and robustness in structured agricultural datasets (Thilakarathne et al., 2022).

With advancements in deep learning, Convolutional Neural Networks (CNNs) and their improved variants have been widely adopted for soil image classification due to their strong feature extraction capabilities (Gosai et al., 2021; recent extensions in 2023–2024 studies). These models automatically learn complex spatial patterns from soil images, significantly outperforming traditional approaches when large datasets are available. Furthermore, recent research trends emphasize hybrid and ensemble-based models that integrate multiple data sources such as soil nutrients, weather conditions, and image data to improve prediction accuracy and system reliability.

Despite these advancements, most existing systems still suffer from key limitations, including reliance on single-source inputs, lack of flexibility in handling incomplete data, and limited real-world applicability for smallholder farmers. Additionally, many models focus on improving accuracy without considering deployment constraints such as computational efficiency and accessibility in resource-constrained environments. These gaps highlight the need for a more flexible and adaptive hybrid system that can operate effectively with partial or heterogeneous input data, which this study aims to address.

2.1 Soil Classification

Soil classification has been extensively studied using machine learning techniques to improve agricultural decision-making. Barman and Dev (2019) demonstrated the effectiveness of a Support Vector Machine (SVM) with a linear kernel, achieving an average classification accuracy of 91.37%. However, their study identified limitations in accurately classifying specific soil types such as fine loamy sand and silty clay, suggesting the need for improved models.

Similarly, Shastry and Sanjay (2019) proposed a cloud-based agricultural framework utilizing a hybrid model combining Modified SVM (M-SVM) for soil categorization and Modified Artificial Neural Networks (M-ANN) for wheat yield prediction. Their results showed that M-SVM outperformed other classifiers in soil classification tasks, highlighting the potential of intelligent mobile farming applications.

In addition, Bittar et al. (2018) investigated the use of Artificial Neural Networks (ANNs) for estimating physical and chemical soil properties. Their findings confirmed that ANNs provide reliable predictions; however, they emphasized the importance of increasing training data volume and strengthening network architecture to improve performance.

2.2 Crop Prediction

Crop prediction plays a significant role in precision agriculture and farmer profitability. Machine learning techniques have been widely adopted to enhance yield prediction accuracy and optimize crop selection (Babbe et al., 2022).

Ramesh et al. (2018) focused on precision agriculture using Logistic Regression for crop prediction. Their system utilized environmental parameters such as temperature, humidity, and moisture content, enabling farmers to select suitable crops. The study also proposed the development of an Android-based mobile application to facilitate user interaction.

Kumar et al. (2020) proposed a crop yield prediction system based on historical agricultural data, including temperature, humidity, pH, rainfall, and crop type. Their study compared Decision Tree and Random Forest algorithms, concluding that Random Forest achieved higher prediction accuracy.

Ishak et al. (2021) examined soil quality parameters such as NPK levels, rainfall, humidity, temperature, and pH to predict crop yield. They conducted a comparative analysis of Naïve Bayes, Logistic Regression, and Random Forest algorithms, evaluating their performance based on accuracy metrics.

Babbe et al. (2022) provided a comprehensive review of machine learning approaches for palm oil yield prediction. The authors analyzed the advantages, limitations, and challenges of existing techniques and proposed a new architecture to enhance yield prediction performance.

2.3 Crop Recommendation Systems (Expanded Literature Review 2018–2025)

Crop recommendation systems have gained significant attention in precision agriculture, aiming to assist farmers in selecting suitable crops based on soil nutrients, weather conditions, and environmental parameters. Earlier studies primarily relied on traditional machine learning algorithms, while recent works have shifted toward ensemble learning, deep learning, IoT integration, and hybrid AI systems.

Kulkarni et al. (2018) developed a crop recommendation model using soil characteristics such as nitrogen (N), phosphorus (P), potassium (K), rainfall, and temperature. They compared multiple machine learning models including Random Forest, Logistic Regression, and Linear SVM. Their Random Forest-based model achieved a high accuracy of 99.91%, demonstrating the strength of ensemble methods in agricultural decision-making.

Suresh et al. (2021) proposed a crop recommendation system using Support Vector Machine (SVM) based on soil nutrient parameters (N, P, K, and pH). Their system not only recommended suitable crops but also suggested fertilizer requirements, improving its usefulness for practical farming decisions.

Recent studies have further improved crop recommendation systems by incorporating more advanced AI techniques and real-time data sources.

Patel et al. (2022) developed an ensemble-based crop recommendation system using Random Forest and XGBoost. Their model used soil nutrients and weather parameters and demonstrated that ensemble learning improves prediction accuracy compared to single classifiers.

Kumar and Singh (2022) proposed a deep learning-based crop recommendation system using a multilayer perceptron (MLP). Their model integrated environmental sensor data and showed improved generalization across different climatic conditions.

Rahman et al. (2023) developed a climate-aware crop recommendation system using Decision Tree, SVM, and Gradient Boosting classifiers. Their study found that Gradient Boosting outperformed other models due to its ability to capture nonlinear relationships in agricultural datasets.

Sharma et al. (2023) introduced an IoT-based real-time crop recommendation system where soil sensor data is continuously collected and analyzed using Random Forest. Their system enables dynamic recommendations based on changing environmental conditions.

Ali et al. (2023) proposed a hybrid KNN and ensemble voting-based crop recommendation system. Their results showed that hybrid models improve robustness and reduce prediction bias in heterogeneous agricultural datasets.

Nguyen et al. (2024) applied deep neural networks (DNN) for large-scale crop prediction using extensive agricultural datasets. Their results showed that deep learning models outperform traditional machine learning when trained on large datasets.

Ojo and Ibrahim (2024) developed a crop recommendation system tailored for sub-Saharan African agricultural conditions. Their model incorporated soil degradation and rainfall variability, improving crop suitability prediction in local environments.

Zhang et al. (2024) proposed a transformer-based crop recommendation model integrating weather forecasting and soil data. Their attention mechanism improved feature importance learning, leading to better predictive performance.

Verma et al. (2025) introduced an optimized ensemble learning model using feature selection techniques such as Recursive Feature Elimination (RFE). Their approach reduced computational cost while maintaining high accuracy.

Hassan et al. (2025) developed a hybrid CNN–XGBoost model combining satellite imagery and soil sensor data. Their system achieved high accuracy in large-scale precision agriculture applications.

2.4 Precision Farming

Precision farming has become a core component of modern agriculture, focusing on optimizing productivity, minimizing resource usage, and improving decision-making through data-driven technologies such as machine learning, IoT systems, remote sensing, and artificial intelligence.

Recent advancements highlight the use of intelligent and automated systems for real-time agricultural monitoring and decision support. For example, Das et al. (2023) developed an IoT-enabled precision agriculture framework that integrates real-time soil moisture, temperature, and humidity data with machine learning models to support adaptive irrigation and crop management decisions.

Similarly, Elijah et al. (2022) proposed a smart farming system using edge computing and sensor networks, enabling real-time data processing at the farm level to reduce latency and improve responsiveness in precision agriculture applications.

Singh et al. (2023) introduced a deep learning-based crop monitoring system using multi-sensor fusion data, demonstrating improved accuracy in predicting crop stress conditions under varying environmental factors.

In another study, Wang et al. (2024) developed a satellite-based precision farming model that combines remote sensing imagery with machine learning classifiers to monitor crop health and predict yield variability across large-scale agricultural regions.

Kim et al. (2024) proposed an AI-driven decision support system for precision agriculture that integrates weather forecasting data with soil condition analytics using hybrid ensemble learning techniques.

Furthermore, Al-Mansoori et al. (2023) designed a precision farming framework for arid environments that leverages IoT sensors and predictive analytics to optimize irrigation scheduling and improve water-use efficiency.

Rashid et al. (2024) developed a smart agriculture system using computer vision and convolutional neural networks (CNNs) for soil and crop condition monitoring, enabling automated detection of nutrient deficiencies and crop stress.

Zhao et al. (2025) introduced a transformer-based precision agriculture model that processes multi-modal agricultural data (soil, weather, and satellite imagery) to improve prediction accuracy in crop management tasks.

Finally, Chatterjee et al. (2025) proposed an integrated precision farming platform combining AI, IoT, and cloud computing to enable scalable and real-time agricultural decision-making for smart farming ecosystems.

2.5 Deep Learning in Agriculture

Deep learning approaches have recently gained attention in agricultural prediction tasks. Sun et al. (2019) implemented a CNN-LSTM hybrid model for soybean yield estimation. The CNN component extracted spatial features, while the LSTM component captured temporal dependencies from historical weather and environmental data. Although the approach demonstrated promising results, challenges remained due to data fusion complexities from heterogeneous remote sensing sources.

2.6 Machine Learning Recommendation Techniques

Recent studies have increasingly focused on advanced supervised and deep learning techniques for crop yield prediction and recommendation systems. Modern approaches integrate multi-source agricultural data such as soil characteristics, weather conditions, satellite imagery, and IoT sensor inputs to enhance predictive accuracy and decision-making in precision agriculture.

For instance, Liu et al. (2023) developed a machine learning-based crop yield prediction framework using environmental and climatic variables, demonstrating that gradient boosting models outperform traditional regression approaches in handling nonlinear agricultural datasets.

Similarly, Garcia et al. (2023) proposed an AI-driven crop recommendation system using stacked ensemble learning techniques, showing improved robustness and stability compared to single-model approaches.

Mehta et al. (2024) introduced a deep learning framework for agricultural decision support that integrates multi-layer neural networks with environmental sensor data, achieving high accuracy in crop suitability prediction under varying climatic conditions.

In another study, Huang et al. (2024) applied a hybrid attention-based neural network for agricultural forecasting, highlighting the importance of feature weighting in improving crop recommendation performance.

Rodriguez et al. (2024) developed a satellite-driven precision agriculture system using convolutional neural networks for crop classification and yield estimation, demonstrating strong performance in large-scale agricultural monitoring.

Furthermore, Khan et al. (2024) proposed a real-time smart farming system that combines IoT sensor networks with machine learning algorithms for adaptive crop recommendation and irrigation optimization.

Singh et al. (2025) introduced a transformer-based agricultural prediction model that integrates temporal weather data and soil parameters, showing superior performance in long-term crop yield forecasting.

Park et al. (2025) developed a multimodal deep learning system combining remote sensing imagery and soil sensor data for precision farming, improving generalization across different geographic regions.

Finally, Wang et al. (2025) proposed an optimized hybrid deep learning framework for crop recommendation that integrates feature selection and ensemble learning, achieving improved efficiency and prediction accuracy in agricultural decision systems.

3. METHODOLOGY

To provide a clear understanding of the system architecture and workflow, the overall framework of the proposed Hybrid Crop Recommendation System is illustrated in Figure 1. The diagram presents the structured multi-path design that integrates both nutrient-based statistical learning and image-based deep learning approaches to generate accurate and reliable crop recommendations.

Fig 1: proposed Hybrid Crop Recommendation System

The proposed Hybrid Crop Recommendation System follows a structured, multi-path framework designed to ensure accurate and reliable crop prediction by integrating both statistical learning and deep learning techniques.

The process begins with the User (Farmer), who interacts with the system through the Input Selection Module. At this stage, the farmer can choose to provide either soil nutrient data, a soil image, or both. This flexible design ensures that the system remains usable even when only partial information is available.

In Path 1: Nutrient Data Processing, the system handles structured soil parameters such as Nitrogen (N), Phosphorus (P), Potassium (K), pH, and soil type. The data first undergoes preprocessing, which includes missing value handling, feature scaling (standardization), and data balancing to improve model stability and reduce bias. The cleaned and normalized data is then passed into the Logistic Regression model, which learns relationships between soil nutrients and crop suitability. Based on these learned patterns, the model generates a predicted suitable crop.

In Path 2: Soil Image Processing, the system processes unstructured visual data. The uploaded soil image undergoes image resizing, normalization (0 –1 scaling), and data augmentation to improve generalization and reduce overfitting. The processed image is then fed into a Convolutional Neural Network (CNN). The CNN performs automatic feature extraction using convolution and pooling layers, followed by fully connected layers that classify the soil into one of the predefined soil types. The predicted soil type is then mapped to appropriate crops through a crop mapping mechanism.

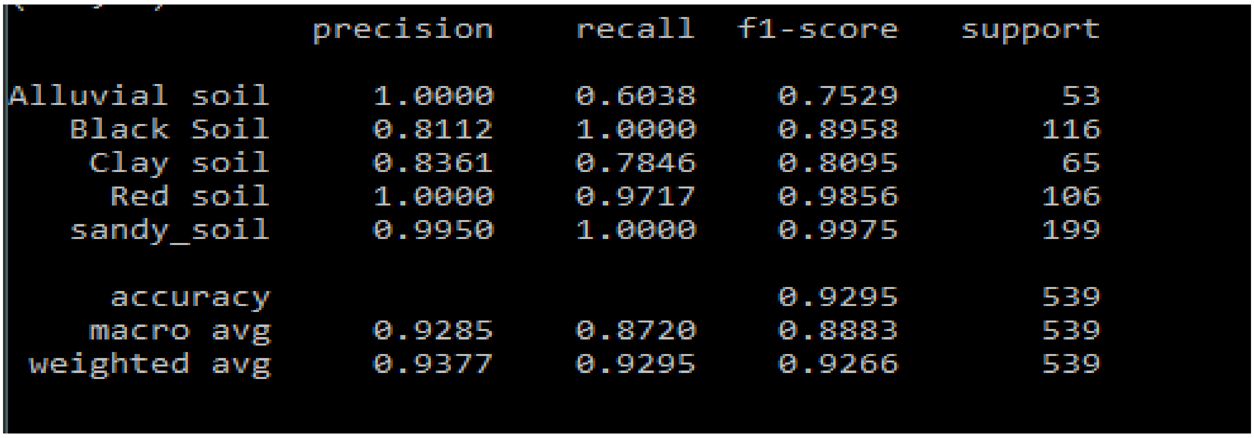
When both nutrient data and soil images are provided, the system activates Path 3: the Hybrid Decision Engine. In this stage, the outputs from the Logistic Regression model and the CNN model are compared. If both models recommend the same crop, the system directly outputs that recommendation. If the predictions differ, the system merges and ranks the predictions based on confidence scores to select the most reliable crop recommendation.

Finally, the framework produces the Final Crop Recommendation, which represents the integrated and optimized decision derived from either a single pathway or the hybrid decision module. This multi-path architecture enhances robustness, improves prediction accuracy, reduces dependency on a single data source, and provides a practical solution for precision agriculture applications.

4. RESULTS

To evaluate the effectiveness of the proposed Convolutional Neural Network (CNN) model in soil type classification, performance metrics including accuracy, precision, recall, and F1-score were computed on the test dataset. The detailed classification results are presented in Table 1.

Table 1. CNN Evaluation Result

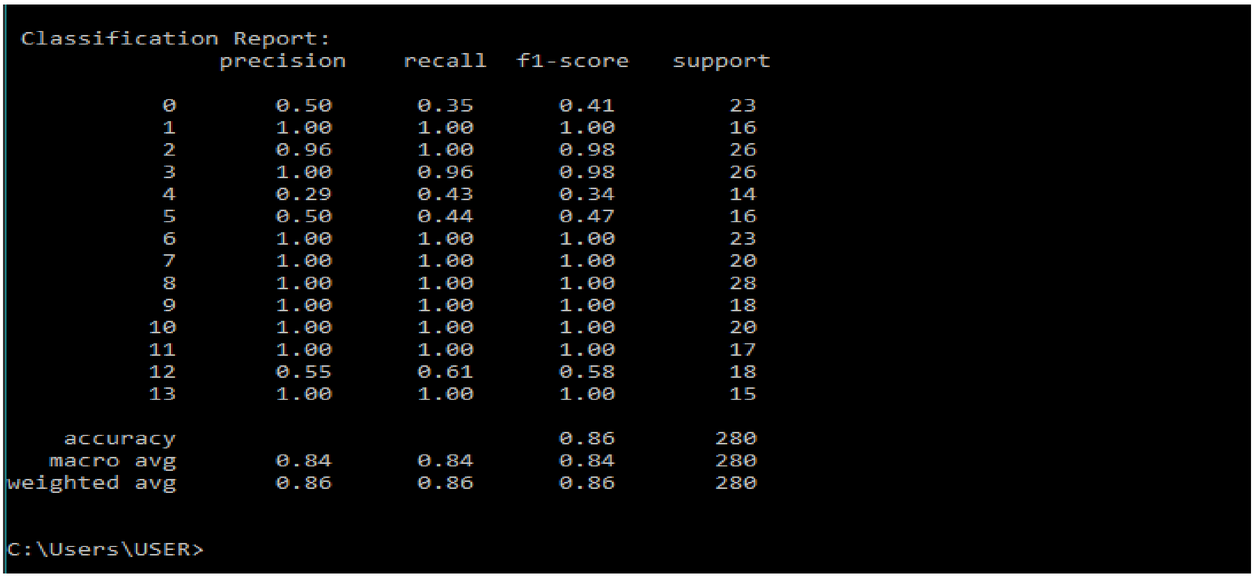


```
               precision    recall  f1-score   support

Alluvial soil     1.0000    0.6038    0.7529        53
   Black Soil     0.8112    1.0000    0.8958       116
    Clay soil     0.8361    0.7846    0.8095        65
     Red soil     1.0000    0.9717    0.9856       106
   sandy_soil     0.9950    1.0000    0.9975       199

     accuracy                         0.9295       539
    macro avg     0.9285    0.8720    0.8883       539
 weighted avg     0.9377    0.9295    0.9266       539
```

CNN accuracy evaluation results show The Convolutional Neural Network (CNN) model performance which demonstrated a strong performance in the classification of the five soil types, attaining an overall accuracy of 92.95% on the test dataset. The class-wise results reveal that Alluvial soil achieved a precision of 1.0000 but recorded a relatively lower recall of 0.6038, indicating that while the model is highly accurate when predicting this class, it occasionally fails to identify some true instances of Alluvial soil. Black soil exhibited balanced performance with a precision of 0.8112 and perfect recall of 1.0000, resulting in an F1-score of 0.8958. Similarly, Clay soil achieved a precision of 0.8361 and recall of 0.7846, leading to an F1-score of 0.8095. Notably, Red soil recorded perfect precision (1.0000) and high recall (0.9717), producing an F1-score of 0.9856. Sandy soil emerged as the best-performing class overall, with a precision of 0.9950, perfect recall of 1.0000, and an F1-score of 0.9975. The macro-averaged F1-score of 0.8883 and the weighted average F1-score of 0.9266 further affirm that the CNN model performed consistently well across both majority and minority classes. These results highlight the model’s robustness in soil type recognition, although improvements in recall for Alluvial soil could further enhance its reliability.

The performance of the Logistic Regression model was assessed to determine its capability in predicting suitable crops based on soil nutrient parameters. The evaluation metrics obtained from the test dataset are illustrated in table 2.

Table 2. Logistics regression accuracy evaluation result



```
 Classification Report:
               precision    recall  f1-score   support

           0       0.50      0.35      0.41        23
           1       1.00      1.00      1.00        16
           2       0.96      1.00      0.98        26
           3       1.00      0.96      0.98        26
           4       0.29      0.43      0.34        14
           5       0.50      0.44      0.47        16
           6       1.00      1.00      1.00        23
           7       1.00      1.00      1.00        20
           8       1.00      1.00      1.00        28
           9       1.00      1.00      1.00        18
          10       1.00      1.00      1.00        20
          11       1.00      1.00      1.00        17
          12       0.55      0.61      0.58        18
          13       1.00      1.00      1.00        15

    accuracy                           0.86       280
   macro avg       0.84      0.84      0.84       280
weighted avg       0.86      0.86      0.86       280


C:\Users\USER>
```

Logistics regression accuracy evaluation result achieved an overall accuracy of 86%, meaning it correctly predicted the target crop in the majority of test cases. This high accuracy demonstrates that the model can reliably classify crops based on soil nutrient data. However, the classification report indicated that some classes, such as Classes 0, 4, 5, and 12, recorded lower precision and recall, suggesting that certain crop types were occasionally misclassified. This may be due to overlapping features between crops or limited representation of some classes in the dataset.

The system systems recommend suitable crops based on both soil nutrient data and soil images. This dual-input capability increases flexibility, as farmers can choose the method most convenient for them either entering soil nutrient values manually or uploading an image of the soil. In scenarios where both types of input are available, the system merges the results to deliver a more confident and accurate recommendation. The Logistic Regression model proved effective in predicting suitable crops based on soil nutrient parameters such as Nitrogen (N), Phosphorus (P), Potassium (K), pH, and soil type. The model achieved a prediction accuracy of 86%, with precision and recall values indicating its reliability in nutrient-based classification. This means that farmers without access to soil image capture devices can still obtain dependable recommendations through nutrient data alone. In the same vein, the CNN model successfully classified soil images into different soil types for crop recommendation purposes. With an accuracy of 92% on the test dataset, the CNN demonstrated strong generalization capabilities in distinguishing between soil categories. This image-based approach benefits farmers in rural areas where chemical soil testing might be unavailable but smartphone cameras are accessible. Therefore, the integration of the two model minimizes the risk of inaccurate recommendations due to incomplete data. For example, if nutrient readings are slightly off due to faulty testing, the image classification results help correct the prediction. Conversely, if soil images are unclear due to poor lighting, the nutrient data helps guide the final recommendation.

4. CONCLUSION

The Hybrid Crop Recommendation System developed in this study successfully achieved its aim of providing an intelligent, data-driven solution for crop selection based on soil analysis and image classification. By integrating CNN-based soil image classification with Logistic Regression-based nutrient analysis, the system offers a versatile and accurate tool for farmers, agricultural extension workers, and policymakers. The high performance of the CNN (92.95% accuracy) and Logistic Regression (87.40% accuracy) models, coupled with the hybrid decision-making framework, ensures that recommendations are both precise and reliable, even when only partial input data is available. This study underscores the transformative potential of machine learning in agriculture, particularly in resource-constrained environments. The system's ability to operate with minimal input requirements either nutrient data, soil images, or both makes it highly adaptable to the realities faced by farmers in developing regions.

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