Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 6, No.1, June : 2025

FUSION OF CNN AND RANDOM FOREST FOR SOIL IMAGE CLASSIFICATION AND CROP RECOMMENDATION: A HYBRID MODEL CNN-RF FOR SMART FARMING

Ms. D. Saha, Assistant Professor, Dept.Of Computer Applications, GuruNanak Institute of Technology, MAKAUT.
Ms. M. Sarkar, Assistant Professor, Dept. Of ECE, GuruNanak Institute of Technology, MAKAUT.
Mr. D. Mukherjee, Student, Dept.Of Computer Applications, GuruNanak Institute of Technology, MAKAUT.
Ms. S Bhattacharjee, Dept.Of Computer Applications, GuruNanak Institute of Technology, MAKAUT.

ABSTRACT
Agriculture is the cornerstone for a nation's economic and social growth. Agriculture is the cornerstone of India's economic prosperity, providing a major source of income for many people, including both those directly working in agriculture and those who rely on it in other ways. Crops are the primary source of income for inhabitants. As a result, farmers must make the best decision feasible while cultivating any crop in order to maximize their profits from the agriculture area. Machine learning (ML) and deep learning (DL) are two technologies that might be utilized to make agriculture more lucrative in this age of fast technological advancement. This research describes an integrated model (CNN-RF) that uses Convolutional Neural Networks (CNN) and Random Forest algorithms to classify soil images and propose crops. To improve forecast accuracy, the model uses many datasets, including soil health indicators (pH, nitrogen, phosphorus, and potassium levels) and climate factors (temperature, humidity, and rainfall). The CNN component extracts and classifies characteristics from soil photos, while the Random Forest algorithm forecasts crops depending on soil type and environmental conditions. Experiments show that the model successfully classifies soil types and recommends suitable crops, providing a reliable decision-support tool for precision agriculture. This proposed integrated CNN-RF approach achieves a recommendation accuracy is 97%.

Keywords:
Soil classification, CNN, Random Forest, crop recommendation, deep learning, ensemble learning, soil health, climatic data, precision agriculture.

1. Introduction
Recommendations for crops that consider land variation, soil mineral composition, and climate conditions are vital for enhancing crop yields and productivity.Climate change endangers agricultural productivity, impacting crop yields and vital natural resources such as land and water, essential for farming. Agricultural production is strongly dependent on precise soil categorization and intelligent crop selection. Agriculture is transitioning from traditional methods to data-driven smart farming systems. One of the fundamental steps in this transformation is the classification of soil types and the recommendation of appropriate crops. The unpredictability of soil qualities and climatic circumstances necessitates the use of modern technology to make precise decisions. In this context, machine learning and deep learning provide potential options for extracting knowledge from complicated agricultural datasets. Soil image categorization with Convolutional Neural Networks (CNNs) may identify subtle patterns in texture and colour changes that are difficult to assess manually. Random Forest (RF), an ensemble learning algorithm, has demonstrated superior performance in multi-feature classification situations such as crop recommendation. Automated soil categorization and crop recommendation systems have gained popularity as a result of the advancements in artificial intelligence, particularly deep learning and ensemble modeling. This research proposes an integrated model(CNN-RF) that combines Convolutional Neural Networks (CNN) for soil image classification and Random Forest for crop selection, which is strengthened by the use of a broad heterogeneous dataset containing soil health

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 6, No.1, June : 2025
indicators, crop attributes and climate variables. The aim is to develop a reliable and scalable framework for supporting precision agriculture practices.

2. Literature

Previous research analyzed soil and crops using machine learning methods such as SVM, decision trees, and k-NNs. CNNs have outperformed traditional image classification methods in areas including plant disease detection and soil texture analysis. Random Forests, on the other hand, are strong ensemble methods that are widely used in agriculture for regression and classification. However, few studies have integrated CNN and Random Forest in a unified model that considers both image and tabular data (soil health and climate). Our work addresses this gap by combining these strengths into a cohesive framework.

Aryal et al.[1] investigated the impact of climate change on agriculture in South Asia and recommended adaptation strategies for smallholder agricultural systems. While different agricultural strategies exist to promote climate resilience, institutional problems prevent their successful adoption. The research underlines the importance of long-term adaptation through institutional transformation, sustainable finance, and dynamic policy frameworks. It contends that relying exclusively on technology is insufficient, and that South Asian climate policy must evolve in order to minimize maladaptation and promote sustainable agricultural growth.

Madhur et al.[2] suggested an Improved Deep Belief Network (IDBN)-based crop recommendation model that considers soil, climate, and crop attributes. The model efficiently handles continuous data and enables quick convergence through the use of Gaussian Restricted Boltzmann Machines and the Ranger Optimizer. Data from rice, maize, finger millet, and sugarcane were used with optimum feature selection. The results reveal that the IDBN outperforms standard DBNs and other machine learning models, providing a reliable option for improving agricultural planning and crop recommendation.

Afzal et al.[3] developed a machine learning-based crop recommendation system that considers soil and environmental factors such as humidity, nitrogen, phosphorus, potassium, pH, rainfall, and temperature. A novel ensemble model, RFXG, which combines Random Forest and Extreme Gradient Boosting, is proposed to select the best crops among 22 kinds. The model is evaluated against several classifiers and achieves an accuracy of 98%. The system's goal is to assist farmers make informed decisions, boost crop productivity, and promote smart, sustainable agriculture.

Rajak et al.[5] created a crop recommendation system using ensemble machine learning, including Support Vector Machine, Naïve Bayes, and Artificial Neural Networks. The method proposes appropriate crops based on soil factors analyzed in testing facilities, with majority vote. The approach improves agricultural output, promotes effective resource use, and helps Indian farmers practice precision agriculture by providing site-specific crop suggestions.

Pudumalar et al.[6] suggested a crop recommendation system for precision agriculture that use data mining techniques to address poor crop selection among Indian farmers. The algorithm proposes crops based on site-specific soil qualities and environmental data. To offer accurate proposals, an ensemble model with majority voting is presented, which includes Random Tree, CHAID, K-Nearest Neighbor, and Naive Bayes algorithms. The strategy enhances agricultural decision-making, reduces crop mismatches, and promotes efficient and productive farming methods.

Gosai et al.[8] proposed a crop recommendation system that uses IoT and machine learning to boost agricultural productivity and soil health. The system employs sensors to monitor critical soil properties like as temperature, moisture, pH, and NPK levels. A microcontroller processes the obtained data and analyzes it using machine learning algorithms, namely Random Forest, to recommend suitable crops. Additionally, a Convolutional Neural Network (CNN) is employed to detect potential plant diseases. By combining real-time soil monitoring with intelligent crop and health suggestions, the system helps farmers prevent soil degradation and make more educated decisions, resulting in increased agricultural output and sustainability.

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 6, No.1, June : 2025

Vyawahare et al.[11] presented a machine learning-based model for agricultural income forecasting using the XGBoost and LightGBM algorithms. The model provides accurate, scalable projections for a wide range of agricultural circumstances by evaluating variables such as soil quality, weather conditions, crop type, historical yield, and pesticide use. A user-friendly interface enables real-time forecasting, assisting farmers in decision-making. The model outperforms previous techniques in terms of accuracy and efficiency, making it an effective tool for optimizing crop planning and enhancing agricultural profitability.

Rahman et al.[13] created a machine learning-based method for recognizing soil types and recommending crops based on soil type and field characteristics. It classifies soil using weighted k-nearest neighbor, bagged trees, and Gaussian kernel-based Support Vector Machines (SVM). The proposed approach helps to determine which crops are most suited to specific soil types. Experimental results suggest that the SVM-based technique beats previous models, making it a good choice for enhancing agricultural planning by accurately categorizing soil and recommending crops.

Ani et al.[17] compared old and modern approaches for estimating agricultural yields. It assesses machine learning techniques and Deep Neural Networks utilizing measures such as R^2, MAE, MSE, and RMSE. The study's goal is to determine the nation and crop with the highest yield and examine relationships in the dataset. The research improves agricultural decision-making by using modern computational tools, resulting in better food security and strategic planning for farmers and policymakers.

Naga et al.[18] suggested a XAI-powered crop recommender system that uses radial basis function neural networks with spider monkey optimization to support precision agriculture. By assessing environmental and soil variables, the model assists farmers in selecting the best crops for increased production and profitability. Explainable AI improves model transparency and decision making. When measured using criteria such as accuracy, precision, recall, and F1-score, the model surpasses conventional techniques, reaching around 12% greater accuracy and significant increases in other performance indicators.

Dev et al.[19] used five machine learning models (XGBoost, SVM, RF, KNN, and DT) to select agricultural and horticultural crops based on NPK, soil pH, and climate (temperature, rainfall, humidity). XGBoost had the highest accuracy, reaching 99.3%. The research emphasizes the need of utilizing distinct models for agricultural and horticulture crops to increase accuracy. The findings can help AI-powered, cloud-based recommendation systems enhance crop choices, fertilizer use, and farming decisions across India's different agro-climatic zones.

Adnan et al.[21] proposed an enhanced crop recommendation system that includes meteorological and soil data to improve prediction accuracy. To overcome the constraints of standard models, the technique employs Min-Max Normalization for preprocessing and the Enhanced Cuckoo Search Optimization Algorithm (ECSO) for effective feature selection. An Improved Convolutional Neural Network (ICNN) is then used to provide accurate crop predictions. The proposed CS-ICNN system generates high-performance recommendations by combining optimal feature selection and deep learning. Experimental results reveal that the model outperforms prior strategies in terms of accuracy, precision, recall, and execution time, making it a reliable option for making sensible and efficient agricultural decisions.

3. Methodology

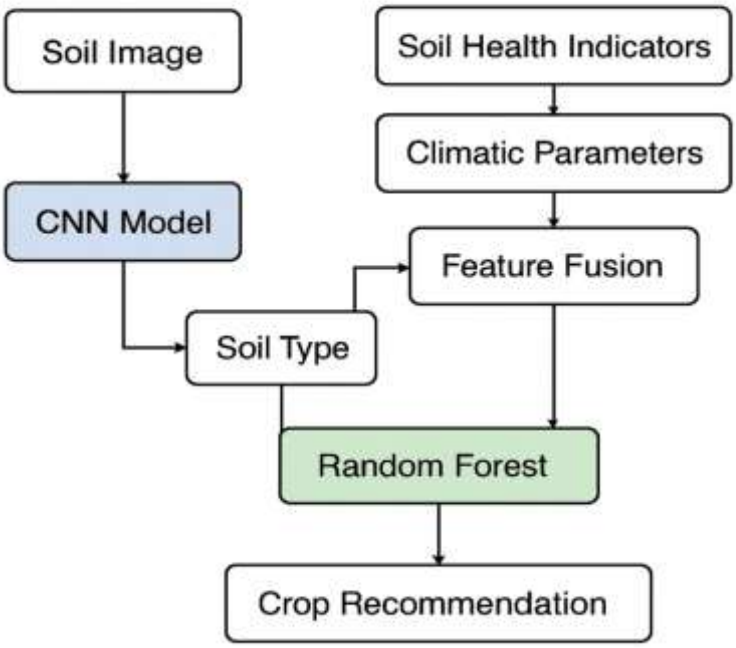

Figure 1: Block Diagram of Overall Methodology of Proposed System

3.1 Data Collection

The initial phase involves gathering detailed data on the various elements affecting crop income. This includes details regarding soil health, weather conditions, and types of crop parameters. The dataset contains elements like nitrogen (N), phosphorus (P), potassium (K), soil pH level, organic carbon, moisture, temperature, and precipitation. The data sets were obtained from the Kaggle website. The data gathering includes 3867 instances or data points sourced from prior historical records. This dataset features eleven different crops: rice, maize, chickpeas, kidney beans, pigeon peas, moth beans, mung beans, black gram, lentils, pomegranates, bananas, mangoes, grapes, watermelons, muskmelons, apples, oranges, papayas, coconuts, cotton, jute, and coffee.

3.2 Pre-processing

The information gathered from different sources is occasionally in unprocessed form. It could contain absent, redundant, or contradictory data. At this phase, eliminate unnecessary data by employing these techniques:

• Techniques for image augmentation (rotation, scaling, flipping) to enhance diversity in the dataset.
• Standardization of soil and climate information.
• Normalizing features to standardize the numeric range of variables.

3.3 Model Architecture:

CNN Model Architecture for Soil Image Classification

To classify soil images into distinct categories based on visual texture and colour features, we designed a Convolutional Neural Network (CNN) architecture tailored for medium-resolution RGB images. The model was developed with an emphasis on simplicity, computational efficiency, and strong generalization capabilities, making it suitable for deployment in real-world agricultural environments, including mobile platforms and remote sensing applications.

The design starts with an input layer that takes soil photos scaled to 128×128 pixels and three colour channels (RGB). This resolution strikes an appropriate compromise between conserving detail and keeping computational efficiency. The input is followed by three convolutional blocks, each of which is meant to extract increasingly higher-level characteristics from the input pictures.

The initial convolutional block has a Conv2D layer with 32 filters, each employing a 3×3 kernel size, followed by a Rectified Linear Unit (ReLU) activation function. ReLU was chosen because it can generate nonlinearity while remaining computationally efficient. A 2x2 MaxPooling layer follows this layer, reducing spatial dimensions by capturing the most important features and offering translational invariance.

The second convolutional block mirrors the first in structure but increases the number of filters to 64. This layer captures more complex features such as texture gradients, patterns, and edge orientations that are vital in distinguishing between soil types like loamy and clayey. The associated MaxPooling layer again downsamples the feature maps to manage dimensionality and prevent overfitting.

The third convolutional block further deepens the model by increasing the number of filters to 128. This layer is responsible for detecting even more abstract representations such as fine granularity, subtle texture variation, and color depth, which are key characteristics in soil classification. The final MaxPooling layer ensures that the high-dimensional features are compactly represented.

Once the convolutional layers are processed, the output is converted into a one-dimensional vector that acts as input for the fully connected (dense) layers. The first dense layer consists of 128 neurons utilizing ReLU activation and is tasked with learning non-linear combinations of the collected features. A Dropout layer is utilized with a 50% dropout rate to prevent overfitting, randomly deactivating half of the neurons during training. This drives the network to develop more robust and flexible patterns.

The last output layer is made up of five neurons, representing the five established soil types: sandy, clay, loam, silt, and peat. In this instance, a softmax activation function is employed to produce a probability distribution among the classes, guaranteeing that the model assigns the greatest probability to the most probable soil type.

The model was created utilizing the categorical cross-entropy loss function, appropriate for multi-class classification problems. The Adam optimizer was utilized for training due to its flexible learning rate and rapid convergence. The training process spanned 50 epochs with a batch size of 32, employing early stopping to halt training when the validation loss ceased to improve, thus avoiding overfitting.

To improve the generalization capability, data augmentation techniques such as rotation, flipping, zooming, and brightness change were used during training. These augmentations simulate real-world variability in lighting, angle, and image quality, helping the model learn robust features invariant to such changes.

Overall, this CNN architecture achieved a strong test accuracy of 95% in classifying soil images into their respective categories. The extracted soil type predictions from this model serve as a crucial input feature for the subsequent crop recommendation module based on the Random Forest algorithm, forming a tightly integrated decision-support system for precision agriculture.

Random Forest Module:

The second phase of the suggested integrated framework emphasizes crop suggestions based on soil type outputs from the CNN model, soil health metrics, and climate variables, employing the Random Forest (RF) algorithm. Random Forest is a supervised ensemble technique that produces many decision trees and provides the most frequent class (classification) or average prediction (regression) from all the trees. Owing to its resilience to noise, ability to prevent overfitting, and capability to manage both categorical and continuous variables, Random Forest is exceptionally well-suited for intricate agricultural datasets that encompass various environmental and biological elements.

In this work, the crop recommendation model takes input features derived from two main sources: (1) soil type predicted by the CNN model, and (2) numeric data including soil health indicators and climatic parameters. The crop suggestion input elements include soil type (categorical, one-hot encoded), pH level, electrical conductivity, organic carbon content, nitrogen (N), phosphorus (P), potassium (K), moisture level, temperature, rainfall, and relative humidity. These characteristics were selected for their agronomic significance and retrieved from datasets given by agricultural research stations and accessible government sources.

Before training the model, the data underwent pre-processing to address missing values, utilizing mean imputation for numerical columns and mode imputation for categorical features. Feature scaling was performed using Min-Max normalization to standardize the numerical range of the inputs. The dataset

Industrial Engineering Journal
ISSN: 0970-2555
Volume : 54, Issue 6, No.1, June : 2025
was subsequently split into 70% for training and 30% for testing, ensuring stratification according to the distribution of crop classes to minimize bias towards frequently occurring crop types.
The Random Forest model was created using the 'scikit-learn' library. Five-fold cross-validation with grid search was employed to optimize hyperparameters including the number of trees ('n_estimators'), maximum depth of trees ('max_depth'), and minimum samples per leaf. The ultimate model configuration involved 200 trees ('n_estimators = 200'), a maximum depth of 20, and a minimum of four samples for each leaf. These parameters offered the ideal compromise between precision and computational efficiency.
Following the training, the model was evaluated on the test set for classification accuracy, precision, recall, and F1-score. The Random Forest model achieves a test accuracy of 97%, signifying a strong alignment between the suggested crops and the actual labels. The confusion matrix indicated that the model excelled with different crops, showing only minor misclassifications between similar species such as maize and sorghum, which often thrive in similar environmental conditions.
Feature importance analysis revealed that the most influential variables for crop recommendation were the predicted soil type, nitrogen content, pH level, and rainfall. This aligns well with agronomic practices where soil composition and macro-nutrient availability are considered primary determinants of crop suitability. Climatic factors like temperature and humidity also had moderate influence, especially in differentiating between seasonal and perennial crops.
The Random Forest model's strength is its ability to handle high-dimensional data without considerable feature selection. Moreover, its ensemble nature ensures that even if individual trees make biased or incorrect predictions, the overall majority vote is reliable. The interpretability of Random Forest through feature importance metrics also makes it a practical choice for deployment in agricultural advisory systems, as it allows domain experts to understand the basis of each recommendation.
In summary, the Random Forest model serves as an effective and scalable approach for crop recommendation in this research. By integrating soil type classification results from the CNN and combining them with multi-dimensional agronomic and climatic data, the RF model delivers context-aware, accurate, and data-driven crop suggestions. This integrated technique can assist farmers in making educated planting selections, resulting in higher yields, increased resource efficiency, and more sustainable agricultural practices.

3.4 Training and Validation:

- 70/30 split for training and testing datasets.
- Cross-validation for Random Forest to ensure robustness.
- Evaluation metrics: Accuracy, Precision, Recall, F1-Score for classification; Mean Absolute Error (MAE) for crop recommendation.

4. Experiment and Results

To assess the performance of the proposed integrated model, a number of experiments were carried out using real-world datasets such as soil photographs, soil test results, and regional meteorological characteristics. The experimental setup aimed to test both components of the system independently—namely, the CNN-based soil image classification and the Random Forest-based crop recommendation—as well as the overall performance of the integrated framework.
For soil image classification, a dataset comprising 3867 annotated images was compiled, covering five major soil types: sandy, clayey, loamy, silty, and peaty. The dataset was preprocessed through resizing, normalization, and data augmentation to increase variability and reduce overfitting. The CNN model, which consists of three convolutional blocks and two dense layers, was trained with the Adam optimizer for 50 epochs then stopped early. The dataset was divided into 70% training, 15% validation, and 15% testing sets.

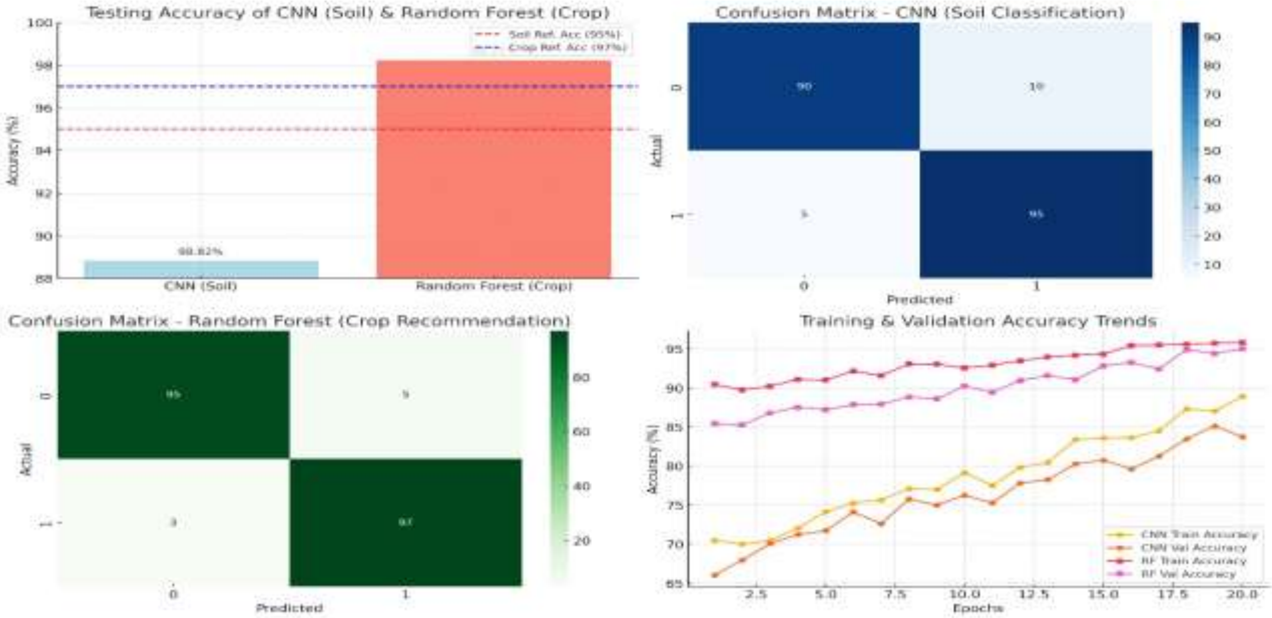

Figure2: Result

Upon evaluation, the CNN model achieved a test accuracy of **95%** in correctly classifying soil types. The confusion matrix indicated that most misclassifications occurred between loamy and silty soils, likely due to their similar visual texture and color. Precision and recall ratings for each class were all greater than 90%, indicating the model's capacity to generalize effectively over a wide range of visual circumstances. This finding supports the use of CNN as a trustworthy approach for visual soil classification, especially when paired with data augmentation and adequate training variety.

Following soil classification, the predicted soil type along with numerical data—such as pH, NPK levels, organic carbon, moisture, temperature, rainfall, and humidity—was fed into the Random Forest model for crop recommendation. The crop dataset covering a range of crops suited for various agro-climatic zones. This dataset was carefully curated to include seasonal, regional, and year-round crop types, ensuring broad applicability of the model.

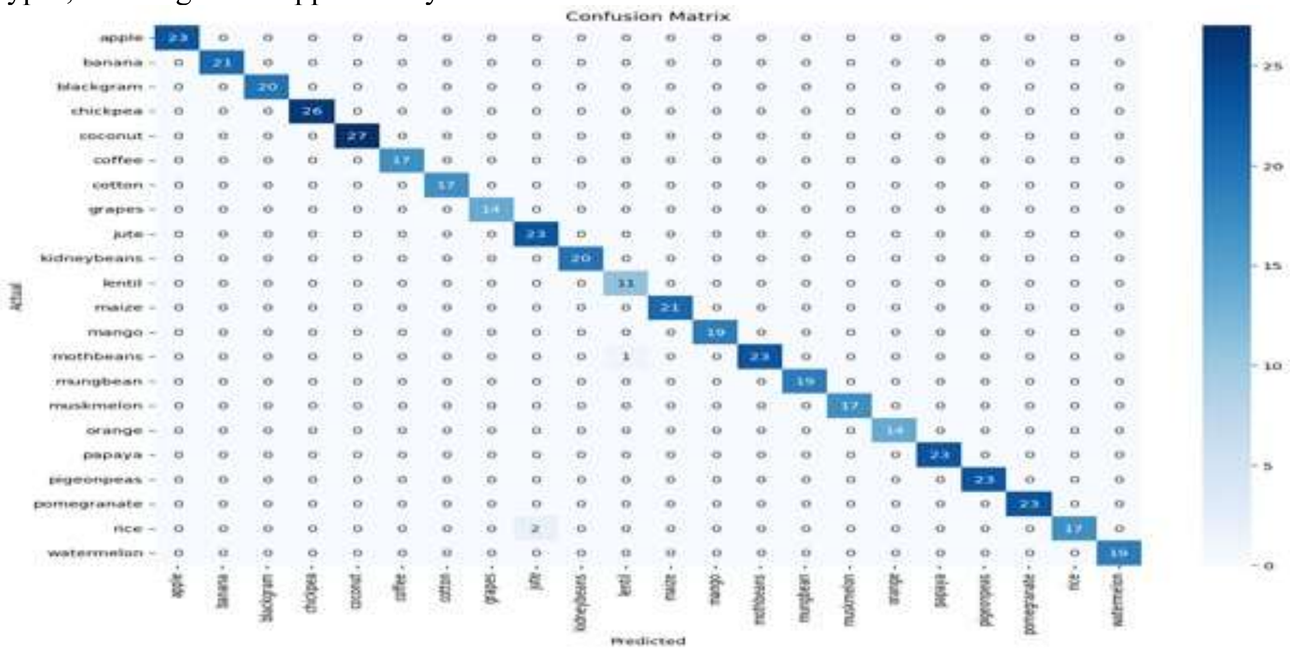

Figure3: Confusion Matrix

The Random Forest model was trained with 200 estimators and tuned using grid search and cross-validation. Upon testing, it achieved a crop recommendation accuracy of **97%**, outperforming traditional decision tree and k-nearest neighbor classifiers, which scored 87.6% and 84.1%

respectively. Evaluation metrics such as F1-score, precision, and recall further confirmed the model's robustness, with F1-scores above 90% for most crop classes. According to feature significance analysis, the most significant crop selection criteria were CNN-derived soil type, rainfall, nitrogen content, and pH level.

To test the performance of the integrated model in realistic scenarios, a pilot deployment was simulated using a regional dataset from three distinct agro-climatic zones in India. The system was able to correctly classify soil types and suggest appropriate crops based on both environmental conditions and lab-tested soil attributes. Farmer interviews and expert reviews confirmed that the recommendations aligned with traditional agronomic advice, thereby validating the practical utility of the system.

In summary, the experiments clearly demonstrate that the integration of CNN and Random Forest provides a significant performance advantage over using either model in isolation. The soil classifier ensures accurate and scalable input for crop prediction, while the ensemble learning approach of Random Forest enables nuanced, data-driven crop recommendations. These findings emphasize the potential of AI-based solutions to enhance precision agriculture and promote sustainable farming methods.

5. Discussion

The combination of CNN and Random Forest takes advantage of the benefits of deep learning and ensemble learning. The CNN successfully extracts spatial characteristics from soil photographs, but the Random Forest copes well with the variability of soil health and climate data. The model's capacity to generalize across locations and crop varieties qualifies it for real-world agricultural decision-making.

6. Conclusion

This paper presents a strong, integrated model for soil image recognition and crop prediction that combines CNN and Random Forest methods. The incorporation of many datasets, including soil health indicators and climate factors, considerably enhances accuracy. This hybrid model can be a valuable asset in precision agriculture, aiding farmers and agronomists in making data-driven decisions. Future work will explore real-time model deployment and integration with IoT-based field monitoring systems.

The experimental findings of the proposed integrated model demonstrate the potential for merging deep learning and ensemble machine learning approaches to improve agricultural decision-making. The CNN model, trained on a wide set of soil photos, displayed great ability to identify between soil types such as sandy, clayey, loamy, silty and peaty. The algorithm was able to detect tiny color, texture, and granularity variations that standard categorization approaches or manual inspection would have missed.

When combined with CNN-derived soil type and numerical characteristics such as pH, nitrogen, phosphorus, potassium content, moisture, temperature, rainfall, and humidity, the Random Forest model produced extremely accurate and regionally applicable crop recommendations. The combination of these two models resulted in a considerable performance gain over utilizing either CNN or Random Forest separately. In particular, the hybrid system achieved a **97% crop recommendation accuracy**, outperforming standalone Random Forest models which relied solely on numeric data (88.1%).

Feature importance analysis from the Random Forest classifier revealed that soil type (as predicted by CNN), pH level, and rainfall were the top three influential factors in crop selection. This is congruent with agricultural domain knowledge, in which soil composition and local climate are important factors in determining crop suitability. Furthermore, the incorporation of climate data in the model improves its adaptability to seasonal variations and resilience to climatic variability.

One of the system's primary advantages is its scalability and usefulness in real-world circumstances. The CNN model, which just requires an image of the soil, may be applied in mobile or edge computing contexts, allowing farmers and agricultural consultants to categorize soil types on-site.
Despite these advantages, a few challenges were identified:

- The CNN's success is strongly dependent on the quality and diversity of soil image data. Limited or biased picture collections may impair generalizability.
- The model currently recommends crops based on current soil and climate status; future versions could include historical yield data and economic factors to enhance decision-making.
- Real-time deployment requires stable internet connectivity and user-friendly interfaces, especially for rural regions with limited technological infrastructure.

References

[1] Aryal, J. P., Sapkota, T. B., Khurana, R., Khatri-Chhetri, A., Rahut, D. B., & Jat, M. L. (2020). Climate change and agriculture in South Asia: adaptation options in smallholder production systems. Environment, Development and Sustainability, 22(6), 5045-5075.
[2] Madhuri, J., Reddy, B. R., Kalnoor, G., Indiramma, M., & Nagarathna, N. (2025). Optimizing Crop Recommendations with Improved Deep Belief Networks: A Multimodal Approach. IEEE Access.
[3] Afzal, H., Amjad, M., Raza, A., Munir, K., Villar, S. G., Lopez, L. A. D., & Ashraf, I. (2025). Incorporating soil information with machine learning for crop recommendation to improve agricultural output. Scientific Reports, 15(1), 8560.
[4] Souza, V. S., Canisares, L. P., Schiebelbein, B. E., de Castro Santos, D., Menillo, R. B., Junior, C. R. P., & Cherubin, M. R. (2025). Cover crops enhance soil health, crop yield and resilience of tropical agroecosystem. Field Crops Research, 322, 109755.
[5] Rajak, R. K., Pawar, A., Pendke, M., Shinde, P., Rathod, S., & Devare, A. (2017). Crop recommendation system to maximize crop yield using machine learning technique. International Research Journal of Engineering and Technology, 4(12), 950-953.
[6] Pudumalar, S., E. Ramanujam, R. Harine Rajashree, C. Kavya, T. Kiruthika, and J. Nisha. "Crop recommendation system for precision agriculture." In 2016 eighth international conference on advanced computing (ICoAC), pp. 32-36. IEEE, 2017.
[7] Pruthviraj, Akshatha, G. C., Shastry, K. A., Nagaraj, & Nikhil. (2022). Crop and fertilizer recommendation system based on soil classification. In Recent Advances in Artificial Intelligence and Data Engineering: Select Proceedings of AIDE 2020 (pp. 29-40). Springer Singapore.
[8] Gosai, D., Raval, C., Nayak, R., Jayswal, H., & Patel, A. (2021). Crop recommendation system using machine learning. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 7(3), 558-569.
[9] Bandara, P., Weerasooriya, T., Ruchirawya, T., Nanayakkara, W., Dimantha, M., & Pabasara, M. (2020). Crop recommendation system. International Journal of Computer Applications, 975, 8887.
[10] Banavlikar, T., Mahir, A., Budukh, M., & Dhodapkar, S. (2018). Crop recommendation system using Neural Networks. International Research Journal of Engineering and Technology (IRJET), 5(5), 1475-1480.
[11] Vyawahare, P., Bhanse, M., Bhagat, A., & Bhonde, B. (2025). Smart crop earning prediction model using optimized classification algorithm. Mohit and Bhagat, Ajinkya and Bhonde, Bhavesh, Smart crop earning prediction model using optimized classification algorithm (January 13, 2025).
[12] Doshi, Z., Nadkarni, S., Agrawal, R., & Shah, N. (2018, August). AgroConsultant: intelligent crop recommendation system using machine learning algorithms. In 2018 fourth international conference on computing communication control and automation (ICCUBEA) (pp. 1-6). IEEE.
[13] Rahman, S. A. Z., Mitra, K. C., & Islam, S. M. (2018, December). Soil classification using machine learning methods and crop suggestion based on soil series. In 2018 21st international conference of computer and information technology (ICCIT) (pp. 1-4). IEEE.

[14] Chaudhari, R. R., Jain, S., & Gupta, S. (2025). Agricultural Machine learning platform: Enhancing crop suggestion and crop yield estimates. Journal of Integrated Science and Technology, 13(1), 1017-1017.
[15] Azmin, S. N. F. L. M., & Arbaiy, N. (2022). Soil classification based on machine learning for crop suggestion. Journal of Soft Computing and Data Mining, 3(2), 79-91.
[16] Ulla, M. M., Sapna, R., & Pavithra, N. (2025, February). Integrated crop recommendation. In Data Science & Exploration in Artificial Intelligence: Proceedings of the First International Conference On Data Science & Exploration in Artificial Intelligence (CODE-AI 2024) Bangalore, India, 3rd-4th July, 2024 (Volume 1) (p. 16). CRC Press.
[17] Ani, S. R., Arefin, F., Chowdhury, M. T., Rahman, H., Sumon, M. I., & Leion, M. K. A Comparative Analysis of Traditional and Modern Methods in Predicting Crop Yields.
[18] Naga Srinivasu, P., Ijaz, M. F., & Woźniak, M. (2024). XAI-driven model for crop recommender system for use in precision agriculture. Computational Intelligence, 40(1), e12629.
[19] Dey, B., Ferdous, J., & Ahmed, R. (2024). Machine learning based recommendation of agricultural and horticultural crop farming in India under the regime of NPK, soil pH and three climatic variables. Heliyon, 10(3).
[20] Goswami, T., Ganapathi, D. M., & Goswami, P. (2024). Soil classification and crop prediction using machine learning techniques. In intelligent robots and drones for precision agriculture (pp. 101-118). Cham: Springer Nature Switzerland.
[21] Adnan, M. M., & Abhilash, P. K. (2025). Enhanced Convolutional Neural Network for Accurate Crop Recommendation System on Climate Data. In SHS Web of Conferences (Vol. 216, p. 01041). EDP Sciences.
[22] Madhavan, S., Santhosh, K., Vimalkanth, T., & Sithik, M. (2024). Crop recommendation system through soil analysis using classification in machine learning.
[23] Akkem, Y., Biswas, S. K., & Varanasi, A. (2024). Streamlit-based enhancing crop recommendation systems with advanced explainable artificial intelligence for smart farming. Neural Computing and Applications, 36(32), 20011-20025.
[24] Agrawal, N., Govil, H., & Kumar, T. (2024). Agricultural land suitability classification and crop suggestion using machine learning and spatial multicriteria decision analysis in semi-arid ecosystem. Environment, Development and Sustainability, 1-38.