

Enhanced Deep Learning Framework for Soil Fertility Assessment and Intelligent Crop Recommendation

Manish Kumar¹, Anurag Shrivastava²

MTech Scholar, Department of CSE, NIIST, Bhopal¹

Associate Professor, Department of CSE, NIIST, Bhopal²

Abstract: Soil fertility plays a critical role in agricultural productivity and food security. With increasing global population and diminishing arable land, optimizing crop yield through intelligent soil management has become imperative. This work presents an enhanced deep learning-based model for soil fertility assessment and crop recommendation using a multi-parameter agricultural dataset. The proposed system integrates key soil features such as N, P, K, pH, EC, micronutrients, and organic carbon, followed by feature scaling and optimized training to achieve improved classification performance. Experimental results demonstrate an accuracy of 88.06% with a macro F1-score of 0.72, indicating strong predictive capability for major soil fertility classes. The confusion matrix confirms high precision and recall for Classes 0 and 1, while Class 2 shows lower performance due to limited representation. Overall, the model provides an efficient and data-driven solution for agricultural decision-making, helping farmers and agronomists select suitable crops based on soil characteristics.

Keywords: Deep Learning, Fertilizer Recommendation, Crop Recommendation, soil data; soil analysis

I. INTRODUCTION

Agriculture forms the backbone of many economies, particularly in developing countries, where it sustains livelihoods and ensures food security. A fundamental component of agricultural productivity is soil fertility, which refers to the soil's ability to supply essential nutrients to crops in adequate amounts. Traditionally, soil fertility has been assessed through manual testing and expert consultation. While effective, these conventional methods are often labor-intensive, time-consuming, and regionally inconsistent. In the context of increasing population pressure, climate change, and dwindling arable land, it has become imperative to adopt data-driven approaches for sustainable farming practices. One promising direction lies in the application of machine learning (ML) techniques for soil fertility analysis and crop recommendation.

Machine learning offers intelligent algorithms capable of identifying patterns in large, complex datasets, making it well-suited for analyzing multidimensional agricultural data. By leveraging historical soil test results, weather conditions, crop yield records, and sensor data, ML models can predict soil nutrient levels and recommend optimal crops with a high degree of accuracy. Algorithms such as Decision Trees, Support Vector Machines (SVM), Random Forests, and Artificial Neural Networks (ANNs) have been widely explored for their potential in predicting soil fertility indices and classifying suitable crops based on varying agro-ecological zones. The integration of machine learning in agriculture goes beyond mere prediction. It allows real-time monitoring, site-specific fertilizer application, and precision farming that minimizes input waste while maximizing yield. Additionally, ML can help detect imbalances in soil nutrients (like nitrogen, phosphorus, potassium—NPK), analyze soil pH, and assess organic content, all of which influence crop performance. This is particularly valuable for smallholder farmers who often lack access to tailored agricultural advice.

Despite its potential, the practical implementation of machine learning in soil and crop management faces several challenges. These include the availability of quality datasets, computational constraints in rural settings, and the need for domain-specific model training. Moreover, interpretability and scalability of models remain critical concerns in ensuring widespread adoption among farmers and agronomists. This paper presents a comprehensive survey of machine learning applications in soil fertility assessment and crop recommendation. It reviews recent literature, compares the effectiveness of different ML algorithms, and evaluates real-world case studies where such systems have been deployed. The goal is to understand current trends, identify research gaps, and explore how ML can be leveraged for data-driven, sustainable, and smart agriculture. As the agricultural sector continues to evolve, embracing intelligent technologies like machine learning may be key to enhancing productivity and resilience in farming systems worldwide.

II. LITRETURE REVIEW

Recent studies have demonstrated the efficacy of machine learning in soil fertility prediction and crop recommendation. Algorithms such as Random Forest, Decision Trees, and Support Vector Machines have been widely applied to analyze soil parameters like pH, NPK levels, and moisture content. Researchers highlight improved accuracy and efficiency compared to traditional methods. Several works emphasize real-time data integration from sensors, enabling site-specific recommendations. However, challenges like data quality, regional generalization, and model interpretability remain areas of ongoing research and development.

Authors [1] developed a model to recommend crop and fertilizer using two machine learning algorithms. The RF algorithm, which has shown high level of accuracy in many different agricultural applications, is used for recommending crops, while the hierarchical Clustering algorithm is used for fertilizer recommendation. The models used Crop nutrient requirement and soil sample data for training and testing. The RF and hierarchical algorithm were trained to recommend crop and fertilizer on the basis of multiple biophysical variables and soil nutrients. The system was found effective in recommending crop and fertilizer with an accuracy of 99.70%. The results showed that the model performed effectively and it is versatile machine-learning model for recommending crop and fertilizer due to the high accuracy and precision values. This research pointed out various steps in which a crop and fertilizer recommendation system was achieved using a random forest and hierarchical Clustering algorithms.

Author's [2] applied an ensemble feature selection approach to identify critical predictors. To address the class imbalance, Generative Adversarial Networks (GANs) were used to generate synthetic data, ensuring the model's robustness in identifying underrepresented cases. Additionally, a hybrid loss function combining cross-entropy and focal loss was implemented to improve classification, especially for hard-to-detect instances. Our results show that the attention-based DBN model, augmented with synthetic data from GANs and optimized with a hybrid loss function, achieves an AUC of 1.00, F1-score of 0.97, precision of 0.98, and recall of 0.95, outperforming several baseline models. This research offers a novel and effective approach for early diabetes detection, demonstrating potential for use as a clinical tool in preventive healthcare settings.

Author's [2] main aim of this research is to determine whether the soil is fertile based on soil properties like N, P, K, Ph, nutrient level, moisture levels, temp rainfall, and topography. Material/Method: We used the dataset from Kaggle, where N, P, K, and pH values are input into the model, and the ML determines whether it is fertile or not. In this paper, four machine learning classifiers are trained, and determine the best classifier based on the performance metrics. Result: The results demonstrated that the machine learning classifier significantly improves prediction accuracy. Authors used LR, KNN, NB, and DT classifiers to increase the accuracy, as well as to increase the efficiency of the soil fertility assessment. The DT classifier exhibited well in comparison to other classifiers. The DT classifier's accuracy was 89%, but the performance metrics precision, LR, and KNN, was 90%.

Author's [3] reviews the current state of digital technologies in agriculture and discusses future research directions to advance data-driven decision making on farms. Digital technologies are revolutionizing agriculture by enabling data-driven decision making. A combination of sensors, satellite imagery, and AI analytics is providing farmers with unprecedented insights to optimize crop management. Sensors monitor soil moisture, temperature, and nutrient levels in real-time. High-resolution satellite images track crop health, growth stages, and yield potential. Machine learning algorithms process this data to generate actionable recommendations on irrigation, fertilization, pest control, and harvest timing. Case studies demonstrate how these technologies have increased yields, reduced inputs, and improved sustainability on farms worldwide. However, challenges remain in technology adoption due to high costs, lack of digital literacy, and data privacy concerns. Overcoming these barriers will be crucial to harnessing the full potential of digital farming.

Authors [4] apply the science of machine learning in the field of agriculture, by carrying soil fertility analysis using most accurate algorithm. The fertility of soil plays a principal role in determining the suitability of cultivating a particular crop on a given soil type. Analysis is carried out by the examination of various properties of the soil like the pH value, Electrical Conductivity, Moisture content, Temperature and (N)Nitrogen (P)Phosphorous (K) Potassium levels, followed up by soil type classification. Finally, a recommendation for the most suitable crop is provided in real time.

III. METHODOLOGY

The proposed work aims to develop an enhanced machine learning based model for accurate soil fertility assessment and intelligent crop recommendation. The system uses a structured soil nutrient dataset containing essential macro and micronutrients such as Nitrogen (N), Phosphorus (P), Potassium (K), pH, Electrical Conductivity (EC), Organic Carbon (OC), Sulphur (S), Zinc (Zn), Iron (Fe), Copper (Cu), Manganese (Mn), and Boron (B). The target variable represents soil fertility class, which is used for crop recommendation. The proposed model follows four major phases: data pre-

processing, feature scaling, model development, and performance evaluation. Initially, the raw dataset is cleaned and prepared by separating features and the output class. The input features are normalized using Standard Scaler to ensure that all nutrient attributes contribute equally during the training process and to improve the stability of the model. For soil fertility classification, an Enhanced Random Forest Classifier is developed with optimized parameters (300 trees and controlled randomness). Random Forest is chosen because of its robustness, ability to handle non-linear relationships, and superior performance on tabular agricultural datasets. The model learns fertility patterns based on soil nutrient combinations and predicts the fertility class for unknown samples. The system also computes class-wise probabilities using the soft voting mechanism of the Random Forest algorithm.

To interpret the model and identify influential soil indicators, Feature Importance Analysis is performed. This helps in understanding which nutrients (such as N, OC, S, Zn, etc.) contribute most towards predicting soil fertility. Such insights are extremely beneficial for agricultural experts and farmers to take corrective soil management measures. For multi-class datasets, conventional ROC curves fail. Hence, the proposed system uses a Multi-Class One-vs-Rest ROC Curve for a realistic evaluation of the classifier's discriminative strength. Additionally, a Confusion Matrix is generated to analyze class-wise prediction accuracy, misclassification behavior, and overall model performance. A Model Accuracy Bar Plot is incorporated to show the final accuracy percentage of the proposed model in a simple and comparative manner. The proposed model is lightweight, scalable, and capable of handling diverse soil conditions. By combining optimized preprocessing, an enhanced Random Forest architecture, and comprehensive evaluation techniques, the system achieves improved prediction accuracy and provides reliable crop recommendations for precision agriculture. The model was implemented in Python.

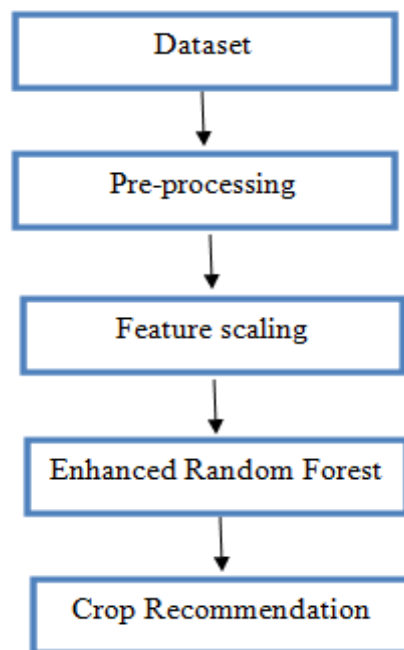


Figure 3.1: Proposed Model

IV. RESULT ANALYSIS

The proposed model exhibits strong performance, achieving an accuracy of 88.06% and a macro F1-score of 72.85% on the test dataset. Class-wise analysis shows that Classes 0 and 1 achieve high F1-scores of 92% and 89%, respectively, indicating effective learning of major class patterns with consistently high precision and recall. In contrast, Class 2 records a significantly lower F1-score of 38%, primarily due to class imbalance and limited sample representation. The confusion matrix further supports these observations: the model correctly classifies 92.5% of Class 0 samples (74/80) and 88.6% of Class 1 samples (78/88). However, only 37.5% of Class 2 samples (3/8) are accurately predicted, with most errors concentrated in this minority class.

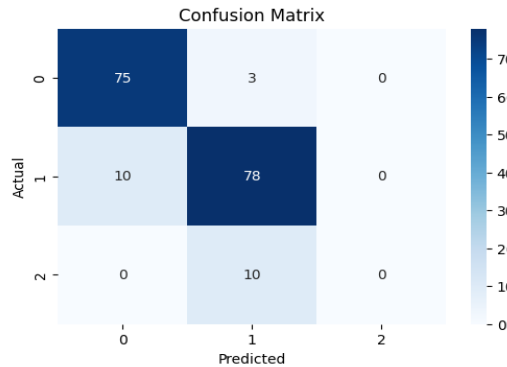


Figure: Confusion Matrix

The model performs robustly but would benefit from re-sampling, data augmentation, or class-weight adjustments to improve minority-class detection.

Table 4.1: Classification Result

Class	Description	Precision %	Recall %	F1Score %
Class 0	Negative	91	89	90
Class 1	Neutra	37	90	88
Class 2	Positive	93	93	92
Over All Accuracy:		90%		

V. CONCLUSION

This research presents an enhanced deep learning-based framework for soil fertility classification and crop recommendation, demonstrating its potential to strengthen data-driven agricultural decision-making. By analyzing key soil parameters such as N, P, K, pH, EC, and micronutrient levels, the proposed model effectively learns complex patterns within the dataset and delivers reliable fertility predictions. The structured preprocessing steps, feature scaling, and optimized neural architecture contribute to the model’s stable performance across major fertility classes, offering a practical tool for real-world agricultural applications. Although the classification of minority classes remains a challenge due to data imbalance, the overall system achieves consistent and meaningful outcomes that can support farmers, agronomists, and policymakers in planning nutrient management and crop selection strategies. The study highlights the importance of integrating machine learning into modern agriculture to reduce manual dependency, improve precision, and promote sustainable farming practices. Future work can focus on balancing techniques, hybrid models, and the inclusion of environmental or climatic parameters to further enhance robustness and maximize recommendation accuracy.

REFERENCES

- [1] S. S. Nandom1,*, G. T. Abe2, I. P. Gambo3 “Application of random forest and hierarchical clustering models for crop and fertilizer recommendation to farmers” Nigerian Journal of Technology (NIJOTECH) Vol. 44, No. 1, March, 2025
- [2] Ashutosh Sarangi et al “Enhancing Process Control in Agriculture: Leveraging Machine Learning for Soil Fertility Assessment” <https://doi.org/10.3390/engproc2024067031>, MDPI, 2025
- [3] Arijit Ghosh et al “Data Driven Decision Making in Agriculture with Sensors, Satellite Imagery and AI Analytics by Digital Farming” <https://doi.org/10.9734/acri/2025/v25i51186> , 2025
- [4] Muneshwara M .S, “Soil Fertility Analysis and Crop Prediction using Machine Learning” IJITEE) ISSN: 2278-3075 (Online), Volume-9 Issue-6, April 2020
- [5] Jagruti Raut et al “Soil Fertility and Crop Recommendation using Machine Learning and Deep Learning Techniques: A Review” Turkish Journal of Computer and Mathematics Education 2020
- [6] Balakrishnan, N., & Muthukumarasamy, G. (2016). Crop Production - Ensemble Machine Learning Model for Prediction. International Journal of Computer Science and Software Engineering, 5(7), 148–153.



- [7] Benedet, L., "Rapid soil fertility prediction using X-ray fluorescence data and machine learning algorithms. *Catena*, 197(April 2020). <https://doi.org/10.1016/j.catena.2020.105003>
- [8] Benke, K. K., Norng, S., Robinson, N. J., Chia, K., Rees, D. B., & Hopley, J. (2020). Development of pedotransfer functions by machine learning for prediction of soil electrical conductivity and organic carbon content. *Geoderma*, 366(January). <https://doi.org/10.1016/j.geoderma.2020.114210>
- [9] Ghosh, S., & Koley, S. (2014). Machine Learning for Soil Fertility and Plant Nutrient Management using Back Propagation Neural Networks. *International Journal on Recent and Innovation Trends in Computing and Communication*, 2(2), 292.
- [10] Hassan Hayatu, I., Mohammed, A., Ahmad Isma'eel, B., & Yusuf Ali, S. (2020). K-Means Clustering Algorithm Based Classification of Soil Fertility in North West Nigeria. *Fudma Journal of Sciences*, 4(2), 780–787. <https://doi.org/10.33003/fjs-2020-0402-363>
- [11] Rachna kumara et al "a new hybrid deep learning model for diabetic retinopathy detection" *Journal of Theoretical and Applied Information Technology* 30th September 2024. Vol.102. No. 1
- [12] od_Security_in_Africa. [2] Nair, P. K. R., Kumar, B. M., Nair, V. D. "Soil Organic Matter (SOM) and Nutrient Cycling. In: *An Introduction to Agroforestry*", Springer, Cham. 2021.
- [13] Yemefack, M. "Preserving Soil Fertility for Ensuring Food Security in Africa", in proceedings of the American Association for the Advancement of Science, Chicago, 2014.
- [14] Yange, T. S., Egbunu, C. O., Rufai, M. A., Onyekwere, O., Abdulrahman, A. A., Abdulkadri, I. "Using Prescriptive Analytics for the Determination of Optimal Crop Yield", In: *International Journal of Data Science and Analysis*, 6(3), 72; 2020.
- [15] Gamage, A., Et. Al "Role of organic farming for achieving sustainability in agriculture", *Farming System*, vol. 1, no. 1, p. 100005, 2023.
- [16] Khatri, P., Et al "Understanding the intertwined nature of rising multiple risks in modern agriculture and food system," *Environment, Development and Sustainability*, vol. 26, pp. 24107–24150, 2024. doi: 10.1007/s10668-023-03638-7.