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Application of AI in Precision Soil Quality Assessment for Sustainable Agriculture

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Abstract

Soil quality assessment is a critical component of precision agriculture and sustainable land management, as soil physicochemical and fertility-related properties directly influence agricultural productivity and environmental sustainability. Conventional soil evaluation methods are often labor-intensive, time-consuming, and difficult to scale across large agricultural regions. This study aims to develop an accurate, scalable, and interpretable artificial intelligence (AI)–based framework for precision soil quality assessment. A comprehensive secondary soil dataset containing physicochemical and fertility indicators was used to classify soil quality into Good, Medium, and Poor categories. Four AI models—Random Forest, XGBoost, Multilayer Perceptron (MLP), and one-dimensional Convolutional Neural Network (1D-CNN)—were implemented and evaluated using an 80:20 stratified train–test split. Model performance was assessed using accuracy, balanced accuracy, precision, recall, F1-score, confusion matrices, Receiver Operating Characteristic curves, and Precision–Recall curves. Results indicate that deep learning models outperform traditional machine learning approaches, with the MLP achieving the highest accuracy, followed by the 1D-CNN. Explainable AI techniques were applied to identify key soil parameters influencing classification outcomes, enhancing model transparency. The proposed AI-based framework demonstrates strong potential for supporting precision agriculture practices and sustainable soil management.

Keywords: Precision Agriculture; Soil Quality Assessment; Artificial Intelligence; Machine Learning; Deep Learning; Explainable AI.

1 Introduction

Long-term food security, ecosystem stability, and agricultural productivity are significantly influenced by soil quality; however, the degradation of soil's physical, chemical, and biological properties caused by intensive farming practices, land misuse, and increasing anthropogenic pressure has highlighted the urgent need for precise and scalable soil quality assessment methods (Abdellatif et al., 2021). Alongside soil degradation, modern agricultural systems are under increasing pressure to enhance productivity while maintaining sustainability, which has accelerated the adoption of advanced computational and data-driven technologies such as artificial intelligence, edge computing, and smart sensing systems (Ajith et al., 2025; Akhtar et al., 2021). Recent advancements in these technologies have enabled real-time soil monitoring and environmental assessment, thereby supporting precision agriculture and sustainable land management practices. In this context, artificial intelligence has emerged as a powerful tool in agriculture by facilitating automated decision-making, predictive analytics, and intelligent analysis of spatial and sensor-based data, particularly through the integration of machine learning and deep learning models(Akter et al., 2024; Ali et al., 2025; Awais et al., 2023). Furthermore, the integration of AI with Internet of Things (IoT) technologies has strengthened precision agriculture systems by enabling smart irrigation, efficient nutrient management, and disease monitoring through real-time data

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acquisition and intelligent analytics, as emphasized in several editorial and conceptual studies highlighting AI-based smart agriculture as a key pathway toward resilient and technology-driven agricultural systems(Bayar et al., 2025; Bhatti et al., 2023). Despite the widespread application of artificial intelligence in precision agriculture, soil quality classification remains relatively underexplored as an independent analytical task, since many existing studies integrate soil assessment with crop management, irrigation systems, or yield prediction, thereby limiting the development of standalone soil-centric analytical frameworks(Hoque & Padhiary, 2024; Howari, 2025). To address this research gap, the primary objective of this study is to develop a framework for classifying soil quality using physicochemical and fertility-related soil parameters through machine learning and deep learning models, enabling accurate, automated, and scalable soil quality assessment suitable for precision agriculture(Bongiovanni & Lowenberg-Deboer, 2004; Botero-Valencia et al., 2025). The scope of this research is specifically focused on soil quality assessment and classification and does not include crop yield prediction, climate analysis, irrigation scheduling, or socio-economic factors. By emphasizing a soil-centric approach and conducting a comparative evaluation of artificial intelligence techniques, this study aims to identify effective models for soil quality analysis and contribute a novel, objective, and scalable framework that supports sustainable soil management and advances data-driven precision agriculture practices (Gupta & Kumar Pal, 2025; Islam et al., 2024).

2 Literature Review

Recent studies indicate a rapid expansion of artificial intelligence–driven smart agriculture systems, particularly those integrating soil analysis with irrigation optimization, fertilizer recommendation, and crop protection strategies. Such AI-based smart agriculture frameworks demonstrate enhanced efficiency by enabling intelligent soil–crop–resource interactions within unified systems(Khaliq et al., 2025). Broader discussions on sustainable and emerging technologies further emphasize the transformative role of artificial intelligence in modern agriculture, highlighting its contribution to long-term sustainability and resilience(Khang et al., 2024). In addition, climate-smart and future-oriented AI-driven farming models underscore the importance of intelligent systems for adaptive soil and crop management under evolving environmental and resource constraints (Kumari et al., 2025).

2.1 AI-Based Smart Agriculture and Soil Analysis Approaches

The theoretical foundation of many AI-driven agricultural systems is rooted in precision agriculture theory, which emphasizes site-specific management of agricultural inputs to address spatial variability in soil properties. This theory provides a conceptual basis for AI-based soil quality assessment by supporting localized and data-informed decision-making. Complementing this, data-driven artificial intelligence theories enable advanced pattern recognition and predictive modeling from complex agricultural datasets, thereby enhancing the analytical capability of precision agriculture systems(Linaza et al., 2021). Studies focusing on soil health and crop protection further highlight the importance of integrating precision agriculture principles with intelligent analytical models to improve soil sustainability and long-term productivity(Mamabolo et al., 2025).

2.2 Limitations of Existing AI-Based Agricultural Studies

Despite significant advancements in smart agriculture technologies, much of the existing literature concentrates on operational efficiency, crop protection, and overall system-level optimization, while comprehensive soil quality classification remains relatively limited. Current studies largely emphasize the general benefits of precision agriculture rather than developing soil-centric analytical frameworks that treat soil quality as an independent analytical task (Mgendi, 2024). Furthermore, although numerous AI-based farming systems have been proposed, comparatively little attention has been given to the systematic evaluation and comparison of multiple artificial intelligence models for soil quality assessment (Mohyuddin et al., 2024). Foundational research on machine learning–based precision farming suggests that intelligent models are capable of managing soil variability and enhancing sustainability outcomes, yet these capabilities remain underutilized within soil-focused analytical frameworks (Sharma et al., 2021). Broader discussions on global food security and AI-enabled sustainable farming further reinforce the potential contribution of soil-centric AI frameworks to resilient agricultural systems (Qaim, 2025; Reddy et al., 2024; Sharma et al., 2024; Sohel et al., 2022; Subić et al., 2025; Zhang et al., 2021).

2.3 Research Gap

Despite significant advancements in artificial intelligence–driven precision agriculture, existing research has largely focused on crop yield prediction, irrigation optimization, and system-level farm management, while soil quality assessment has often been treated as a supporting component rather than an independent analytical task. Many studies integrate soil analysis with crop or climate variables, which limits the development of soil-centric frameworks capable of evaluating soil quality on its own. Furthermore, although various machine learning and deep learning models have been applied in agricultural contexts, there is a lack of systematic comparative evaluation of multiple AI techniques specifically for soil quality classification using physicochemical and fertility-related soil parameters. The limited application of explainable artificial intelligence in soil quality assessment further restricts transparency and practical adoption in decision-support systems. Additionally, existing approaches often struggle with scalability and generalizability across diverse soil conditions. These gaps highlight the need for a standalone, interpretable, and scalable AI-based framework that focuses exclusively on soil quality classification to support precision agriculture and sustainable soil management.

2.4 Research Questions

- How effectively can artificial intelligence models classify soil quality using physicochemical and fertility-related soil parameters?
- How do different machine learning and deep learning models compare in terms of performance for soil quality classification?
- Which soil parameters contribute most significantly to soil quality classification outcomes?
- Can explainable artificial intelligence techniques improve the interpretability of AI-based soil quality assessment models?
- How suitable is an AI-based soil quality classification framework for supporting precision agriculture and sustainable soil management?

2.5 Research Objectives

- To develop an artificial intelligence–based framework for classifying soil quality using physicochemical and fertility-related soil parameters.
- To evaluate and compare the performance of machine learning and deep learning models for soil quality classification.
- To identify the most influential soil parameters affecting soil quality classification outcomes using explainable artificial intelligence techniques.
- To assess the effectiveness of AI-based soil quality classification in supporting precision agriculture and sustainable soil management.
- To examine the scalability and applicability of the proposed AI framework across diverse soil quality classes.

3 Materials and Methods

3.1 Study Area

The study does not focus on a single geographic region; instead, it utilizes a large-scale simulated soil dataset representing diverse soil conditions from various locations across the globe. The dataset comprises one million soil samples generated to reflect realistic variability in soil properties observed under different environmental and agricultural settings. Geographic representation is ensured through the inclusion of latitude and longitude coordinates for each soil sample, allowing the dataset to capture a wide range of soil textures, fertility levels, and physicochemical characteristics commonly found in global agricultural landscapes. The simulated samples cover variations in soil depth, texture classes, nutrient availability, moisture status, and structural properties, thereby representing heterogeneous soil environments relevant to precision agriculture and sustainable land management. By incorporating global-scale variability rather than site-specific conditions, the study area is conceptually defined as a generalized global agricultural context. This approach supports the development and evaluation of scalable artificial intelligence models for soil quality assessment that are not constrained to a particular region and are potentially applicable across diverse agroecological zones.

3.2 Study Design

This study adopts a quantitative and experimental research design to evaluate the effectiveness of artificial intelligence techniques for soil quality classification. The research is based on secondary data analysis using a large-scale simulated soil dataset, which enables objective and reproducible experimentation. The study is experimental in nature, as it involves the development, training, and evaluation of multiple machine learning and deep learning models for multi-class soil quality classification. Soil quality categories serve as the dependent variable, while physicochemical and fertility-related soil parameters are treated as independent variables. No intervention or field-based data collection was conducted; instead, computational modeling and statistical evaluation were employed to assess model performance. A stratified train–test split strategy was used to ensure balanced representation of soil quality classes during model training and validation. This study design supports scalable analysis, unbiased model comparison, and reliable assessment of artificial intelligence–based approaches for precision soil quality assessment and sustainable agricultural decision-making.

3.3 Sample Size and Selection

The study utilizes a large-scale simulated soil dataset comprising one million soil samples, ensuring sufficient data volume for robust training and evaluation of artificial intelligence models. Each sample represents a unique soil profile characterized by physicochemical, structural, and fertility-related attributes relevant to soil quality assessment. The large sample size reduces the risk of data sparsity, enhances model generalization, and supports reliable multi-class classification. Since the dataset is synthetically generated, no probabilistic field sampling was required. Instead, all available soil records were considered for analysis. To ensure fair and unbiased model evaluation, a stratified sampling strategy was employed during data partitioning, preserving proportional representation of soil quality classes across subsets. The dataset was divided into training and testing sets using an 80:20 ratio, with 80% of the samples used for model training and validation and the remaining 20% reserved for independent performance evaluation. This sampling strategy supports balanced learning and reliable comparison among different AI models.

3.4 Research Tools and Techniques

All data preprocessing, model development, and performance evaluation were conducted using the Python programming language. Machine learning and deep learning models were implemented using established open-source libraries to ensure reproducibility and analytical rigor. Random Forest and Multilayer Perceptron classifiers were developed using the Scikit-learn framework, while gradient boosting–based classification was performed using XGBoost. Deep learning experiments were carried out using PyTorch/TensorFlow to develop a one-dimensional Convolutional Neural Network (1D-CNN). Data handling, cleaning, and transformation processes were performed using NumPy and Pandas libraries. To enhance model transparency and interpretability, SHAP (SHapley Additive exPlanations) was employed as an explainable artificial intelligence technique to identify influential soil parameters affecting classification outcomes. Prior to model training, the dataset underwent systematic preprocessing to ensure data quality and effective model learning. Categorical soil attributes were transformed using one-hot encoding, while numerical features were standardized to facilitate stable and efficient training of neural network–based models. Soil quality classes were converted into numerical labels through label encoding. To maintain balanced representation of soil quality categories across datasets, a stratified train–test splitting strategy was applied, preserving class distributions between training and testing subsets.Four artificial intelligence models—Random Forest (RF), XGBoost, Multilayer Perceptron (MLP), and one-dimensional Convolutional Neural Network (1D-CNN)—were developed and evaluated to assess their effectiveness in soil quality classification. Model performance was evaluated using multiple metrics, including accuracy, balanced accuracy, macro-averaged precision, recall, and F1-score. In addition, confusion matrices, Receiver Operating Characteristic (ROC) curves, and Precision–Recall curves were analyzed to provide a comprehensive and unbiased comparison of classification performance across the different models. Figure 1 shows the overall workflow of the proposed AI-based soil quality assessment framework, illustrating the flow from soil indicator inputs through AI-based modeling to final soil quality classification.

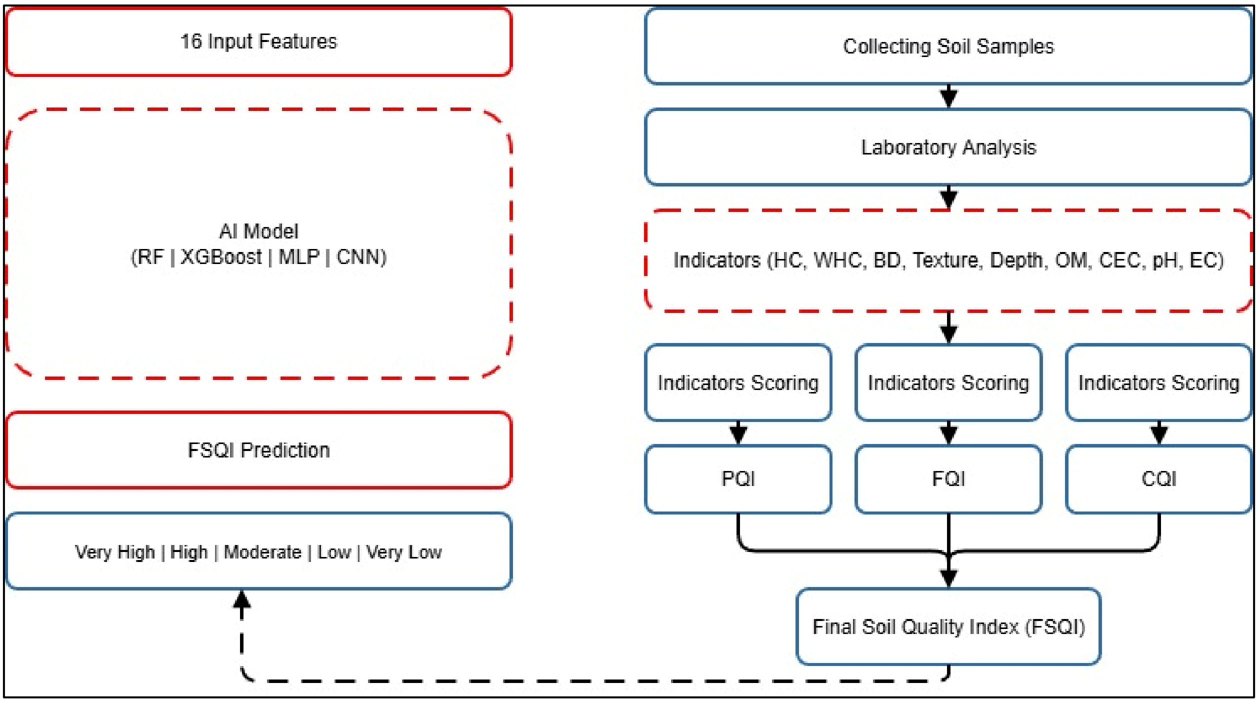

Figure 1 Proposed AI-based Framework for Precision Soil Quality Assessment

3.5 Development of Model

A conceptual artificial intelligence–based soil quality assessment model was developed by integrating soil physical, chemical, and fertility-related indicators with machine learning and deep learning algorithms. The proposed framework maps multidimensional soil attributes to discrete soil quality classes, enabling precision-based agricultural decision-making and supporting sustainable agricultural practices. The conceptual structure and information flow of the proposed framework are illustrated in Figure 1, which demonstrates how soil indicators are processed through different AI models to generate final soil quality categories. This study is based on the assumption that artificial intelligence–based models can effectively classify soil quality using physicochemical and fertility-related soil parameters. It is further expected that deep learning models, particularly the Multilayer Perceptron (MLP) and the one-dimensional Convolutional Neural Network (1D-CNN), will outperform traditional machine learning approaches such as Random Forest and XGBoost due to their ability to capture complex nonlinear relationships among soil attributes. Additionally, the study assumes that explainable artificial intelligence techniques can successfully identify key soil properties influencing soil quality classification, thereby enhancing model transparency, interpretability, and practical applicability in precision agriculture and sustainable land management.

4 Results and Analysis

The experimental results demonstrate that all implemented AI models are capable of classifying soil quality using soil physical, chemical, and fertility-related indicators. However, notable performance differences were observed among the models. Neural network–based approaches, particularly the Multilayer Perceptron (MLP) and the one-dimensional Convolutional Neural Network (1D-CNN), achieved substantially higher classification accuracy compared to the tree-based models. This indicates the superior ability of neural architectures to capture complex nonlinear relationships among soil properties. Although Random Forest and XGBoost exhibited comparatively lower accuracy, they showed stable and consistent performance, confirming their suitability as baseline models for soil quality classification.

4.1 Descriptive Analysis of Soil Parameters

Before evaluating the performance of artificial intelligence models, a descriptive analysis was conducted to examine the distribution and variability of soil physicochemical and fertility-related parameters used in this study. Table 1 presents the summary statistics of key soil attributes, highlighting substantial variation across parameters that are critical for soil quality assessment and model learning.

Table 1 Descriptive Statistics of Soil Parameters

Parameter (Unit)	Mean ± SD	Min–Max
Depth (cm)	17.50 ± 7.22	5.00–30.00
pH	6.50 ± 1.44	4.00–9.00
Organic Matter (%)	5.50 ± 2.60	1.00–10.00
Moisture Content (%)	19.99 ± 8.66	5.00–35.00
Bulk Density (g/cm^3)	1.20 ± 0.23	0.80–1.60
Nitrogen, N (ppm)	102.58 ± 56.31	5.00–200.00
Phosphorus, P (ppm)	30.01 ± 11.55	10.00–50.00
Potassium, K (ppm)	249.88 ± 86.56	100.00–400.00
CEC (meq/100g)	25.01 ± 8.66	10.00–40.00
Electrical Conductivity (dS/m)	2.55 ± 1.41	0.10–5.00
Porosity (%)	37.50 ± 7.21	25.00–50.00
Water Holding Capacity (%)	40.01 ± 11.54	20.00–60.00

4.2 Distribution of Categorical Soil Attributes

In addition to numerical soil parameters, the dataset includes categorical attributes that represent soil texture and color. The distribution of these categorical variables is summarized in Table 2 & 3, indicating a balanced representation across different soil classes and reducing the risk of bias during model training.

Table 2 Distribution of Categorical Soil Attributes (Soil Texture)

Category	Count	Percentage (%)
Sandy	333,463	33.35
Loamy	333,363	33.34
Clayey	333,174	33.32

Table 3 Distribution of Categorical Soil Attributes (Soil Color)

Category	Count	Percentage (%)
Red	250,178	25.02
Yellow	249,991	25.00
Black	249,988	25.00
Brown	249,843	24.98

4.3 Model Performance Evaluation

Figure 2 illustrates the training and validation accuracy curves of the four AI models. The learning curves indicate stable convergence behavior without significant overfitting, suggesting effective model training. The MLP and CNN models demonstrate faster convergence and higher validation accuracy, while Random Forest and XGBoost show more gradual learning patterns.

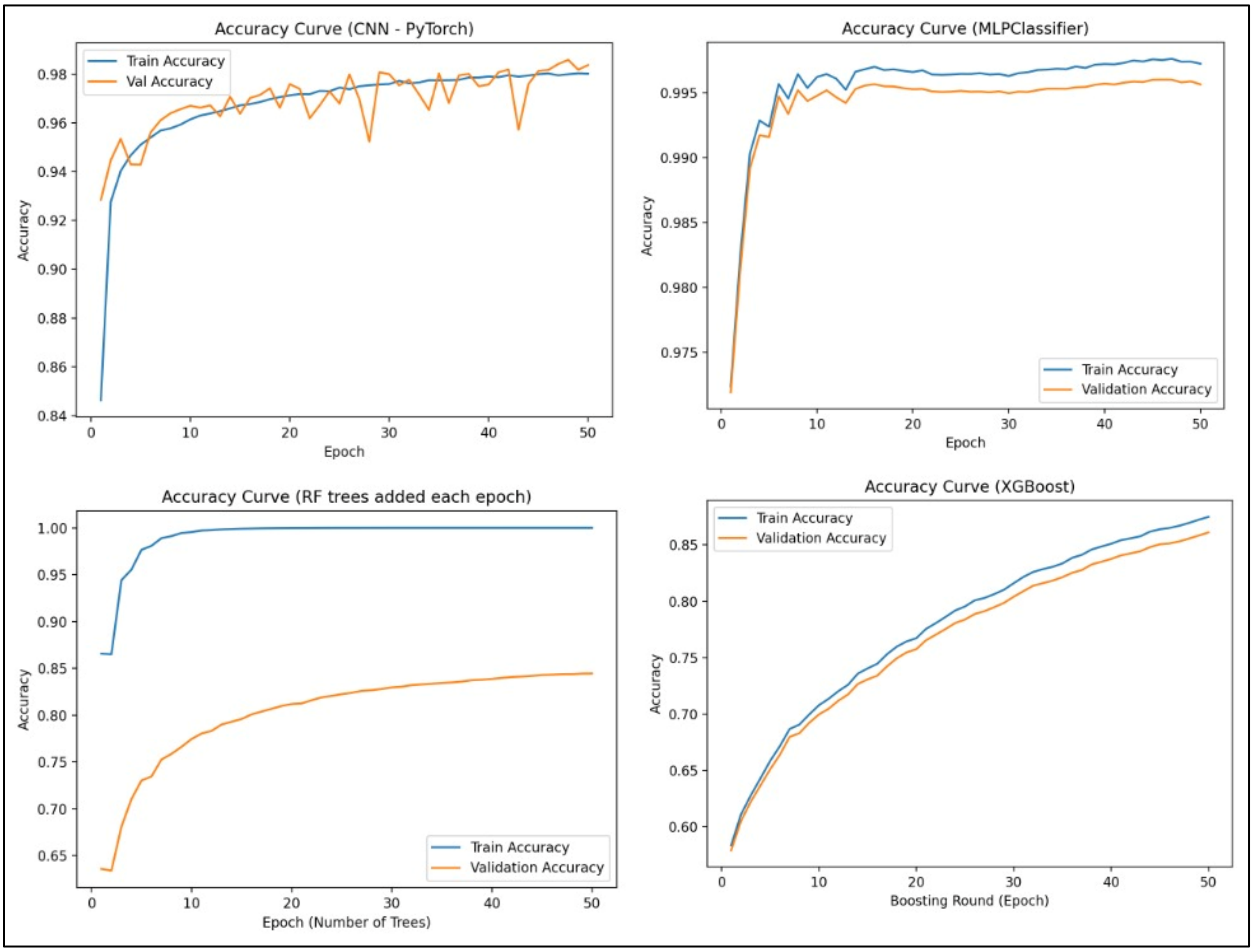

Figure 2 Training and Validation Accuracy Curves

Figure 3 presents the confusion matrices for all models on the test dataset, highlighting strong diagonal dominance for neural models and slightly higher misclassification rates for tree-based models, particularly between adjacent soil quality classes. Overall, these results confirm that AI-based approaches are effective for precision soil quality assessment and that neural models provide enhanced predictive capability for sustainable agricultural applications.

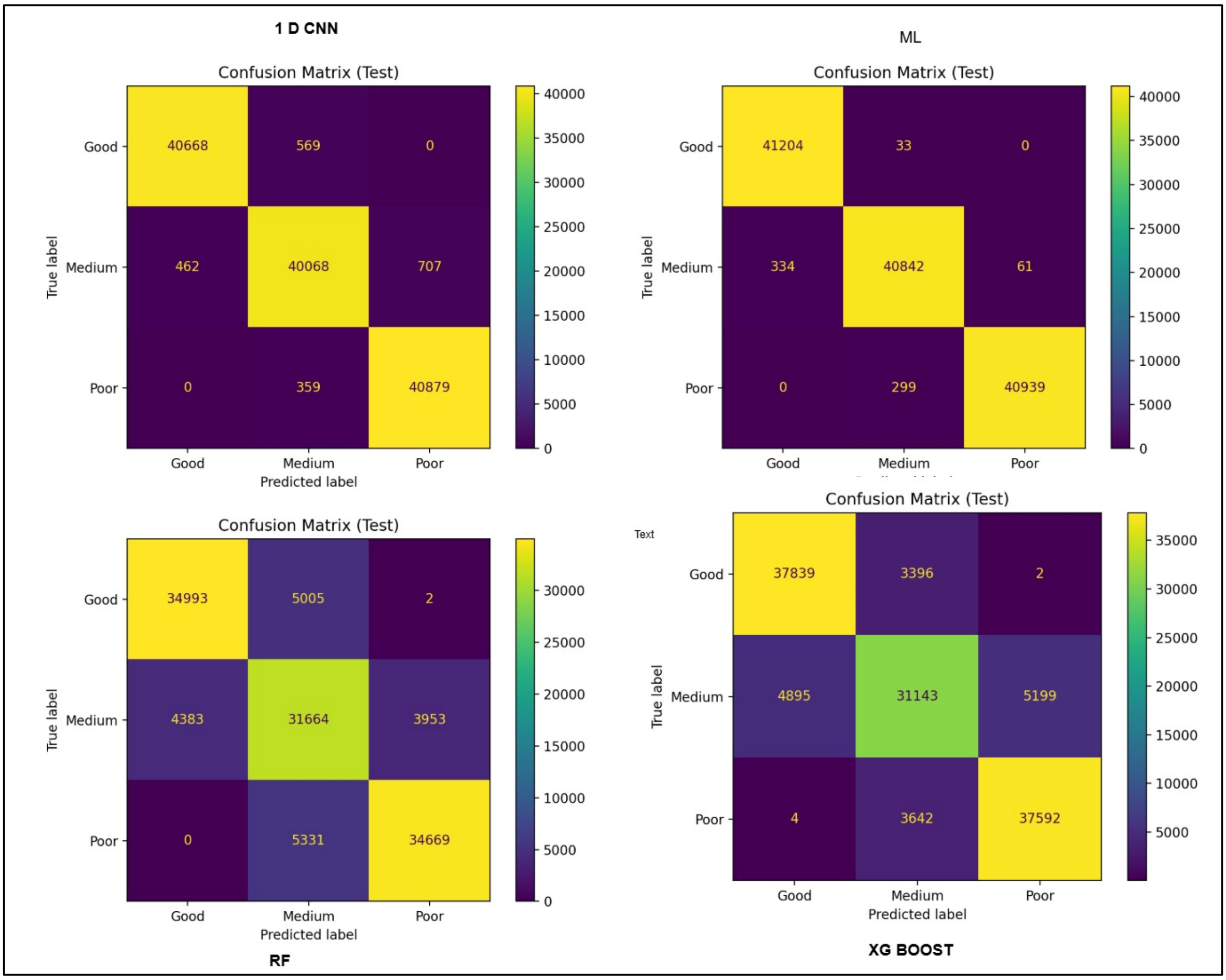

Figure 3 Confusion Matrices of the Four AI Models

5 Discussion

The findings of this study demonstrate that artificial intelligence–based approaches can effectively support soil quality classification by capturing complex interactions among physicochemical and fertility-related soil parameters (El Behairy et al., 2024). The strong performance of deep learning models highlights their ability to model nonlinear relationships that are often difficult to represent using conventional statistical or rule-based methods, reinforcing recent trends in AI-driven precision agriculture (Sharma et al., 2023).The results further suggest that integrating AI models into soil assessment workflows can enhance site-specific decision-making and improve the scalability of soil monitoring systems. Adaptive and self-learning AI frameworks have been emphasized as a promising direction for managing spatial and temporal variability in agricultural environments, particularly under real-time field conditions (Olabimpe Banke Akintuyi, 2024). In this context, AI-based soil classification can serve as a foundational component for broader smart farming systems. Moreover, combining AI-based soil quality assessment with sensor-based crop monitoring and IoT-enabled management platforms can improve irrigation, fertilization, and field surveillance practices. Prior research indicates that intelligent sensing and monitoring systems enhance the responsiveness and efficiency of precision agriculture interventions at the farm level (Sharma & Shivandu, 2024). Since soil quality assessment is directly linked to nutrient management decisions, integrating soil classification outputs with precision fertilizer optimization strategies may contribute to improved nutrient-use efficiency and environmental sustainability(Cai et al., 2025). Similarly, AI-driven nutrient analysis approaches can support optimized cultivation practices by enabling more targeted and data-driven fertilizer recommendations (D et al., 2025).Emerging literature also highlights opportunities to extend AI-based soil assessment beyond physicochemical indicators toward biological dimensions of soil health, such as microbial dynamics, enabling a more holistic understanding of soil systems (Pace et al., 2025). Overall, the proposed framework contributes to sustainable agriculture by supporting soil-informed decision-making and promoting long-term sustainability within modern digital farming ecosystems (Zhang et al., 2024).

5.1 Findings

This study demonstrates that artificial intelligence–based models can effectively classify soil quality using physicochemical and fertility-related soil parameters.

- All implemented models—Random Forest, XGBoost, Multilayer Perceptron (MLP), and one-dimensional Convolutional Neural Network (1D-CNN)—successfully performed multi-class soil quality classification.
- Deep learning models, particularly MLP and 1D-CNN, achieved significantly higher classification accuracy compared to traditional machine learning approaches.
- Neural network–based models showed superior capability in capturing complex nonlinear relationships among multidimensional soil attributes.
- The use of a large-scale dataset comprising one million soil samples enhanced model robustness and generalization performance.
- Descriptive analysis revealed substantial variability across soil physicochemical and fertility parameters, highlighting the importance of multidimensional soil indicators for quality assessment.
- Balanced distributions of categorical attributes such as soil texture and soil color contributed to unbiased model training and stable classification outcomes.
- The application of explainable artificial intelligence techniques enabled the identification of key soil parameters influencing soil quality classification.
- The proposed AI-based soil quality assessment framework provides a scalable and automated alternative to conventional, labor-intensive soil evaluation methods.
- Overall findings confirm that AI-driven soil quality classification can effectively support precision agriculture practices and sustainable soil management.

5.2 Recommendations

Artificial intelligence–based soil quality assessment frameworks should be integrated into precision agriculture systems to enable rapid, objective, and scalable soil evaluation across large agricultural areas.

- Deep learning models, particularly Multilayer Perceptron (MLP) and one-dimensional Convolutional Neural Network (1D-CNN), are recommended for deployment in soil quality classification tasks due to their superior predictive performance.
- Explainable artificial intelligence techniques should be incorporated into AI-driven soil assessment tools to enhance model transparency, interpretability, and user trust among farmers, agronomists, and policymakers.
- Agricultural decision-support systems should prioritize soil-centric analytical frameworks rather than treating soil assessment as a secondary component of crop or irrigation management.
- Large-scale and diverse soil datasets should be utilized to improve model generalization and robustness across different agroecological conditions.
- Future implementations of AI-based soil assessment tools should combine model predictions with agronomic expertise to support context-aware and practical decision-making.
- Policymakers and agricultural institutions should promote the adoption of AI-enabled soil quality monitoring systems to support sustainable soil management and resource-efficient farming practices.
- Standardization of soil data collection and preprocessing protocols is recommended to ensure interoperability and reproducibility of AI-based soil assessment models.
- Researchers are encouraged to extend soil quality classification frameworks toward continuous soil quality index prediction for more granular soil health evaluation.
- Integration of additional environmental and management factors in future studies is recommended to further enhance the applicability and decision-support capability of AI-driven soil quality assessment systems.

6 Limitations

- This study relies on a simulated soil dataset, which, although large and diverse, may not fully capture the complexity and variability of real-world field conditions.
- The proposed framework focuses on soil quality classification into discrete categories rather than predicting a continuous soil quality index, which may limit fine-grained soil health interpretation.
- Environmental and management factors such as climate variability, cropping history, and irrigation practices were not incorporated into the models.
- The analysis was conducted using a single dataset, which may limit the generalizability of the findings across different agroecological zones.

- Model performance was evaluated using an 80:20 train–test split without external validation on independent datasets.
- Although explainable artificial intelligence techniques were applied, deeper causal interpretations of interactions among soil, environmental, and crop-related factors remain limited.

7 Conclusion

This study proposed an artificial intelligence–based framework for precision soil quality assessment using comprehensive soil physicochemical and fertility-related attributes. The experimental results confirm that AI models are effective in soil quality classification, directly supporting precision agricultural practices. A comparative analysis of four AI models—Random Forest, XGBoost, Multilayer Perceptron (MLP), and one-dimensional Convolutional Neural Network (1D-CNN)—demonstrated that neural network–based approaches outperform traditional tree-based classifiers, with the MLP achieving the highest classification accuracy, followed closely by the 1D-CNN. Although tree-based models exhibited comparatively lower accuracy, they provided stable baseline performance. The integration of explainable AI techniques enhanced the interpretability of the proposed framework by identifying key soil parameters influencing soil quality classification, thereby improving model transparency and stakeholder trust. Overall, the findings indicate that AI-driven soil quality assessment can serve as an accurate and interpretable tool for precision agriculture and sustainable soil management. Future research should focus on extending the proposed framework to multi-regional and multi-climatic soil datasets to improve generalizability. Additional directions include continuous Soil Quality Index prediction, integration of climatic and land management factors, and exploration of hybrid deep learning models to further enhance soil quality assessment performance.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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