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Optimizing Soil Fertility through Machine Learning: Enhancing Agricultural Productivity and Sustainability

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Abstract: Nowadays, the sustainability of agriculture and food security have an increasing importance on soil fertility. Soil fertility is defined as the capacity of a land to grow crops and its potential crop productivity. However, factors such as increasing population, climate change, land use changes and environmental pollution threaten soil fertility. These threats can result in problems such as erosion, soil salinisation and organic matter depletion. Soil fertility is critical for the long-term health of agriculture and food security.

This study investigates the application of machine learning algorithms to optimize soil fertility, a critical factor in sustainable agricultural practices and food security. The research utilizes a dataset comprising 880 samples, each containing 12 different soil properties, including nutrient levels, pH, and organic carbon, to develop predictive models. Three machine learning algorithms Extra Trees, Random Forest and K-Nearest Neighbors (KNN) were employed to classify soil fertility and identify the key factors influencing it. Results indicate that the Extra Trees and Random Forest models exhibited superior performance, with the Extra Trees model achieving a high accuracy rate of 0.90 and a mean squared error of 0.09. The feature importance analysis identified Boron as the most influential variable, while Electrical Conductivity was deemed less significant. These findings demonstrate the potential of machine learning to enhance soil management strategies, offering a promising approach to improving agricultural productivity and sustainability. Future research should focus on expanding the dataset and applying these models across various agro-ecological zones to validate their adaptability.

Keywords: Soil Fertility, Machine Learning, Precision Agriculture, Artificial Intelligence, Sustainable Agriculture

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1. INTRODUCTION

Nowadays, the sustainability of agriculture and food security are gaining increasing importance with regard to soil fertility. Soil fertility is defined as the capacity of a land to grow crops and its potential crop productivity. This soil fertility is determined by the interaction of a number of factors, including physical, chemical and biological properties. However, in recent years, factors such as increasing population, climate change, land use changes and environmental pollution threaten soil fertility. Maintaining soil fertility is critical to the long-term health of agriculture and human nutrition. Fertile soils contribute to stable crops across cropping seasons and contribute to ensuring food security of societies. However, problems such as erosion, soil salinisation and organic matter depletion can reduce soil fertility and threaten the long-term sustainability of agriculture.

Soil fertility refers to the ability of soil to support optimum plant growth. It is influenced by various factors such as organic matter content, nutrient availability, pH and biological processes. Intensive agricultural practices have led to a decline in soil fertility due to erosion, loss of organic matter and deterioration of soil properties (Patzel et al., 2000). Cover crops have been used to improve soil fertility by increasing organic matter content, nutrient availability and cation exchange capacity (Solomon, 2023). Soil fertility can be assessed by methods such as soil sampling, heating and titration to detect nutrient levels and organic matter content (Peng Chunjian, 2018). Furthermore, advances in technology have led to the development of electronic devices and systems that use image analysis to determine soil fertility based on colour values (Zhaorong et al., 2018). In general, soil fertility is a complex concept involving the interaction of environmental, physical and chemical factors and plays a crucial role in supporting plant growth (Henis, 1986).

Intensive agricultural practices have led to a decline in soil fertility, primarily due to soil erosion, loss of organic matter and degradation of soil physical, chemical and biological processes and properties. Cover crops have traditionally been used to improve soil fertility. Cover crops can serve as a valuable source of phosphorus (P) and reduce the need for inorganic P fertilisers for subsequent crops. Soil pH, an important indicator of nutrient availability and soil fertility, can be influenced by cover crops. Cover crops release nutrients through residue decomposition after termination, and factors such as cover crop residue quality, soil texture, biological activity and climatic conditions can influence the rate of nutrient release (Solomon, 2023).

Soil fertility is determined by the interaction and interweaving of physical, chemical and biological substances, and biological fertility is one of the least understood components. Soil microorganisms such as bacteria, actinobacteria, fungi, soil algae and soil protozoa play a crucial role in maintaining soil fertility and nutrient cycles. Understanding soil microbiology is essential for sustainable agriculture and meeting the needs of a growing world population (Nadarajah, 2022).

Soil fertility is a fundamental property of every soil type and is determined using various physiochemical methods for the purpose of applying soil fertilisers for plant nutrition. The soil fertility parameters tested include pH in potassium-chloride (KCl), CaCO3, humus, total nitrogen, P2O5 and K2O. The results of the research show that soil fertility is high in many places studied, but there are also areas that require remedial measures (Majstorović et al., 2022).

Soil fertility plays a very important role in agriculture and artificial intelligence (AI) techniques have been applied to improve soil fertility management. Various AI algorithms such as artificial neural networks (ANN), decision trees, random forests and k-nearest neighbours have been used to predict soil fertility and recommend the best crops to farmers (Sunori et al., 2022) (Swetha et al., 2023). These algorithms categorise soil into different categories by analysing soil data, including pH value, available potassium content and other factors, and provide accurate recommendations for crop selection (Swetha et al., 2023). Furthermore, machine learning algorithms such as logistic regression, support vector machines and ensemble techniques have been used to categorise soil into healthy and unhealthy categories based on chemical fertility and other characteristics (Patil, 2022). An approach combining deep learning, artificial intelligence (AI) and the Internet of Things (IoT) has been presented to provide fast and accurate results for soil fertility testing and crop recommendations and overcome the disadvantages of traditional soil testing practices (D N & Choudhary, 2021). The integration of AI with Internet of Things (IoT) technologies has also been investigated to optimise irrigation and fertilisation processes by assessing soil nutrients and moisture content in real time. These advances in AI have the potential to improve soil fertility management and increase agricultural productivity (Nyakuri et al., 2022).

Soil testing is an effective tool for evaluating soil nutrient levels and calculating the appropriate quantity of soil nutrients based on fertility and crop requirements (Raman & Chelliah, 2023). In order to classify village-wise soil nutrient levels and soil fertility indices, a group of 20 classifiers, including bagging, random forest (RF), AdaBoost, support vector machine (SVM), and neural network (NN), were employed, and the class label was evaluated on a scale of high, low, and medium according to their numerical value (Escorcia-Gutierrez et al., 2022). A soil classification method based on principal component analysis (PCA) based laser-induced breakdown spectroscopy (LIBS) and random forest (RF) algorithm was proposed, and the standard soil samples from six different mining areas were accurately identified and classified(Jin et al., 2023). Soil fertility capability classification (FCC) is a technical system to group the soils according to the kind of physical and chemical constraints they present under agronomic management (Hota et al., 2022). Remote sensing techniques based on machine learning algorithms can be used to predict and assess the physical and chemical parameters of the soil, which is extremely important for the fertilization process in precision agriculture(Radočaj et al., 2022).

Machine learning algorithms have materialized in soil fertility prediction as an encouraging method for enhancing production (Rajamanickam & Mani, 2021). Conditional inference tree (CIT) is a machine learning method able to untangle complex interactions while providing an interpretable model (Bastos et al., 2021). Soil parameters such as nitrogen, phosphorus, potassium (NPK), pH, organic carbon, moisture content, and few more things are considered for predicting the fertility of the soil and also to predict the right crops to be grown and nutrition required for it (Varshitha & Choudhary, 2022). Compared with other optimizer models, the adopted method is more suitable for the accurate classification of soil erosion, and can provide new solutions for natural soil supply capacity analysis, integrated erosion management, and environmental sustainability judgment(Chen et al., 2021). Since Machine Learning could play a key role in reducing the costs and time needed for a suitable site investigation program, the basic ability of Machine Learning models to classify soils from Cone Penetration Tests (CPT) is evaluated (Rauter et al., 2021). Features are independent variables such as climatic, edaphic or managerial data, indices or categories, soil tests, and tissue tests (Parent et al., 2021). proposed a model to estimate soil organic matter, total nitrogen, and total carbon where remote sensing data were used as inputs to a support vector machine and an artificial neural network to determine these three soil attributes (Sarkar et al., 2022).

Five machine-learning models – K-nearest neighbor (KNN), multilayer perceptron neural network (MLP), random forest

(RF), support vector machines (SVM), and extreme gradient boosting (XGB) – combined with the original data and three log-ratio transformation methods – additive log ratio (ALR), centered log ratio (CLR), and isometric log ratio (ILR) – were applied to evaluate soil texture and PSFs using both raw and log-ratio-transformed data from 640 soil samples in the Heihe River basin (HRB) in China (Zhang et al., 2020). It includes the identification of land arable, diversification of crops, restoration of organic matter, and rationalization of soil input (Kalyani & Prakash, 2020). In this paper, surface soil moisture was retrieved from Radarsat-2 and polarimetric target decomposition data by using semiempirical models and machine learning methods (Acar et al., 2020).

2. MATERIAL AND METHOD

This study presents a dataset analysis in which various chemical and physical parameters are analysed to determine soil fertility.

2.1. Dataset

The dataset used for this model is the Soil Fertility dataset (https://www.kaggle.com/datasets/rahuljaiswalonkaggle/soil-fertility-dataset). The dataset consists of 880 samples and 13 different properties are measured for each sample. These properties consist of Nitrogen (N), Phosphorus (P), Potassium (K), pH, Electrical Conductivity (EC), Organic Carbon (OC), Sulfur (S), Zinc (Zn), Iron (Fe), Copper (Cu), Manganese (Mn), Boron (B) and fertility as given in Table1 These data show that several chemical and physical parameters are important variables related to soil fertility. For example, nutrients such as Nitrogen and Potassium as well as pH and Organic Carbon levels directly affect productivity. The study results can provide an important basis for optimising soil management and fertilisation strategies.

The following table provides the descriptive statistics of the soil fertility data:

Table 1. Features of the data set

Variable	Mean	Standard Deviation	Min	Max	Units
N	246.74	77.39	6	383	mg/kg
P	14.56	21.97	2.9	125	mg/kg
K	499.98	124.22	11	887	mg/kg
pH	7.51	0.46	0.9	11.15	-
EC	0.54	0.14	0.1	0.95	dS/m
OC	0.62	0.84	0.1	24	%
S	7.55	4.42	0.64	31	mg/kg
Zn	0.47	1.89	0.07	42	mg/kg
Fe	4.14	3.11	0.21	44	mg/kg
Cu	0.95	0.47	0.09	3.02	mg/kg
Mn	8.67	4.30	0.11	31	mg/kg
B	0.59	0.57	0.06	2.82	mg/kg
Productivity Output	0.59	0.58	0	2	-

This table provides a general overview of the distribution of the soil fertility data and presents the basic statistical summary for each variable.

2.2. Machine-learning models and parameter optimization

Machine learning models Extra Trees, Feature Importance, K-Nearest Neighbors (KNN) and Random Forest (RF) used in this study.

2.2.1. Extra Trees

To classify soil fertility using Extra Trees machine learning methods, researchers can leverage the robustness and efficiency of this ensemble learning algorithm. Extra Trees, also known as extremely randomized trees, construct multiple decision trees randomly from the training dataset. This approach is particularly beneficial in soil fertility classification tasks due to its ability to handle high-dimensional data and reduce overfitting (Geurts et al., 2006).

By utilizing Extra Trees, researchers can improve the accuracy of soil fertility predictions by combining the outcomes of independent decision trees into a forest (Ekinci, 2022). This ensemble technique enhances the reliability of classifications by aggregating the outputs of multiple trees, thereby enhancing overall predictive performance (Ali et al., 2023). Additionally, Extra Trees can aid in feature selection, enabling the identification of the most significant soil properties influencing fertility levels (Baby et al., 2021). Figure 1 shows the structure of the Extra Trees method.

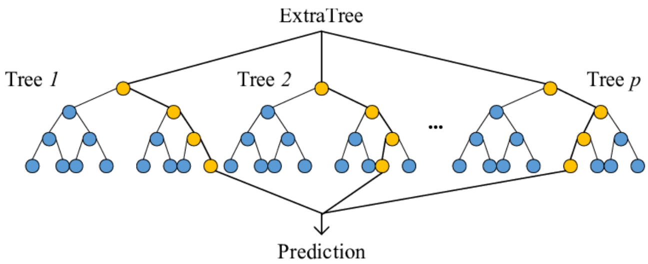


Figure 1. Extra Trees method (Chu et al., 2021)

2.2.2. Feature Importance

To classify soil fertility using Feature Importance machine learning methods, researchers can leverage the significance of relevant features in predicting soil fertility levels. By employing feature importance techniques, such as Mean Decrease in Impurity (MDI) measures, researchers can identify the most influential soil properties that contribute to soil fertility classification (Ahmadi et al., 2020). This approach aids in selecting the most relevant features while excluding irrelevant or redundant ones, thereby enhancing the accuracy and efficiency of the classification model (Talasila et al., 2020).

Furthermore, integrating Feature Importance methods with machine learning algorithms like Random Forest, Support Vector Machines, or Extreme Learning Machines can optimize the soil fertility classification process (Bondre & Santosh Mahagaonkar, 2019). By combining Feature Importance techniques with these algorithms, researchers can prioritize the most critical soil parameters for predicting soil fertility levels accurately (Trontelj Ml & Chambers, 2021). This integration ensures that the classification model focuses on the key features that significantly impact soil fertility, leading to more precise predictions (Suruliandi et al., 2021).

2.2.3. K-Nearest Neighbors (KNN)

To classify soil fertility using the K-Nearest Neighbors (KNN) machine learning method, researchers can benefit from its simplicity and effectiveness in handling classification tasks. KNN is a non-parametric algorithm that categorizes data points based on the majority class of their nearest neighbors (Li et al., 2008). This method is particularly useful for soil fertility classification as it considers the similarity of soil samples based on their features, making it suitable for identifying patterns in soil properties that determine fertility levels (Koren et al., 2024).

By applying the KNN algorithm to soil fertility classification, researchers can leverage its ability to handle both classification and regression tasks (Shakeel et al., 2019). This flexibility allows for predicting soil fertility levels based on the characteristics of neighboring soil samples, enabling accurate classification of soil fertility into different categories (Li et al., 2008). Additionally, KNN can be used to identify hidden patterns in soil data, aiding in the discovery of relationships between soil properties and fertility levels (Raikwal & Saxena, 2012). The working system of the KNN model is given in Figure 2.

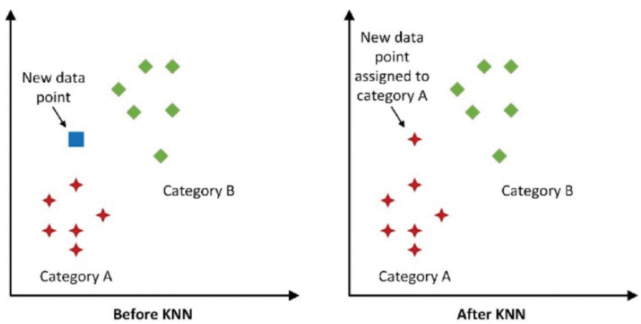


Figure 2. The working system of the KNN model (Aghaabbasi et al., 2023)

2.2.4. Random Forest (RF)

Random Forest is a robust machine learning algorithm that has demonstrated significant potential in soil fertility classification. Random forests are an ensemble learning technique that combines multiple decision trees, with each tree being built based on a random vector sampled independently (Breiman, 2001). This methodology has proven successful in various fields, including ecology, where it has shown effectiveness as a statistical classifier (Cutler et al., 2007).

In the realm of soil fertility classification, Random Forest has been employed to enhance predictions by taking into account the significance of different soil properties. Research has consistently shown that Random Forest outperforms other algorithms, such as linear regression, in predicting soil properties across various depths (Hengl et al., 2015). By utilizing the ensemble approach of Random Forest, researchers can achieve more precise predictions by aggregating the results of multiple decision trees. The working principle of the Random Forest model is given in Figure 3.

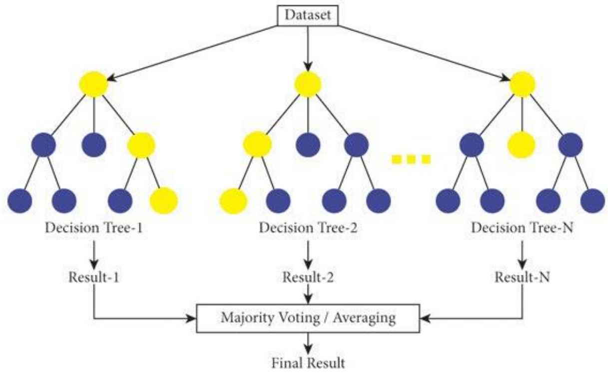


Figure 3. Working principle of the Random Forest model (Khan et al., 2021)

3. RESULTS

In this study, the classification algorithms Random Forest, K-nearest neighbour and extra trees were employed on the soil fertility dataset. GridSearchCV was utilised to optimise the performance of the classification algorithms. GridSearchCV is designed to identify the most effective combinations through cross-validation on a specified grid of hyperparameters. The final hyperparameters were selected by evaluating the model on metrics such as accuracy, F1 score and error rate.

The analysis of soil fertility data using machine learning algorithms yielded significant results. Specifically, the Extra Trees model demonstrated outstanding performance with a Mean Squared Error (MSE) of 0.09, Root Mean Squared Error (RMSE) of 0.30, and an R-Squared value of 0.74, indicating perfect prediction accuracy. Additionally, the accuracy of the Extra Trees model was found to be 0.90. The training results of the Extra Trees model shown in Figure 4.

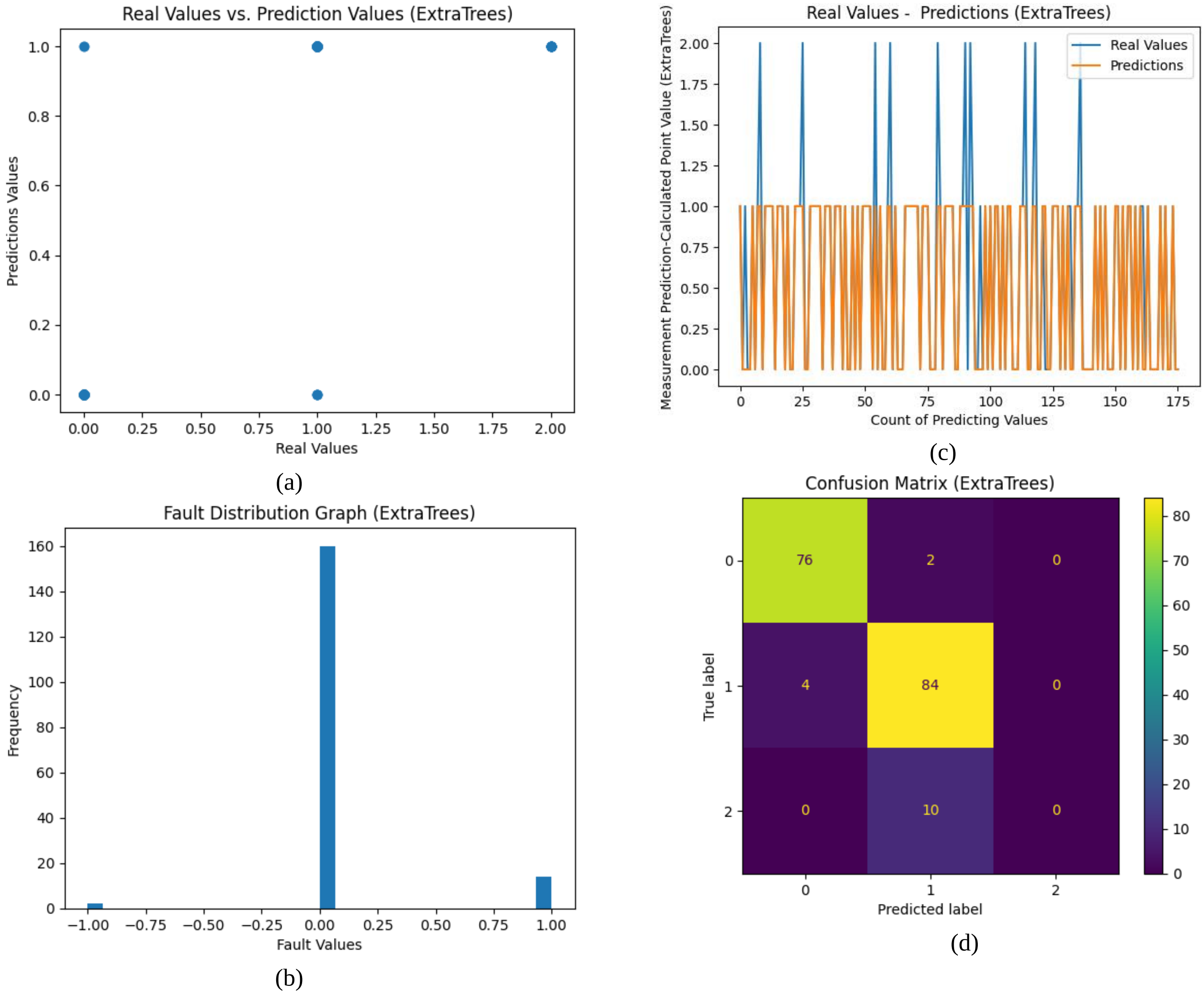
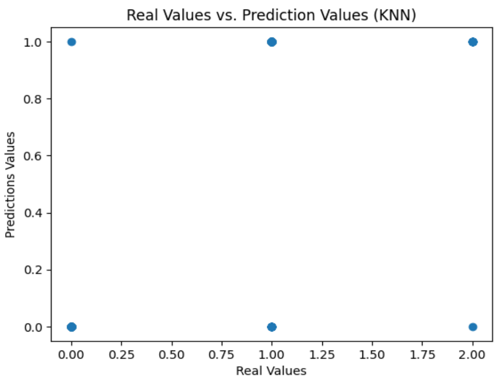


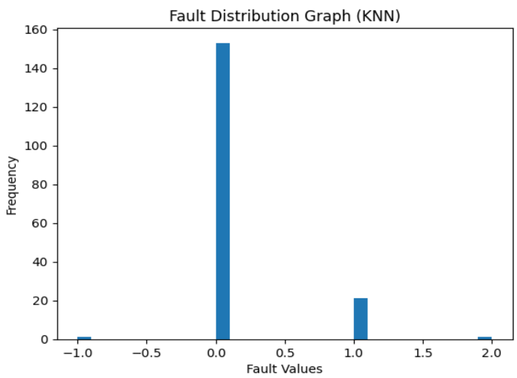
Figure 4. Extra Trees model training results (a. Prediction Graph, b. Error Distribution Graph, c. Prediction Accuracy Graph, d. Confusion Matrix Graph)

The confusion matrix in Figure 4(d) reveals a high-performance model that achieves an accuracy of 0.909. The matrix shows how well the model predicts the actual class labels (True labels) in three categories (0, 1 and 2). The rows represent the true labels, while the columns show the predicted labels. Each cell shows the number of instances classified accordingly. In general, the model performs well for classes 0 and 1, but struggles for class 2, where it fails to predict correctly. The unbalanced performance, especially for class 2, suggests that potential improvements are needed, such as addressing class imbalance or increasing the sensitivity of the model to this class.

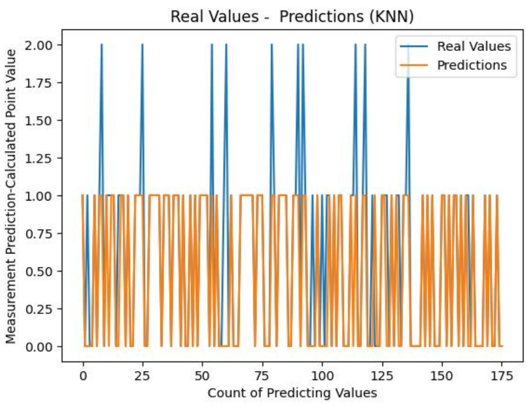
Further comparative analysis between different machine learning models highlighted the efficiency of the Random Forest (RF) and K-Nearest Neighbors (KNN) models. The KNN model achieved an accuracy of 0.869, while the RF model achieved a perfect accuracy of 0.969. These results affirm the superior predictive capability of the RF model in classifying soil fertility based on the dataset used. Figure 5 shows the results of KNN and Rf models in comparison.



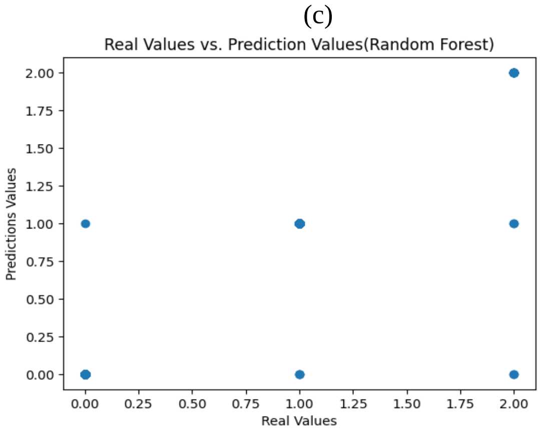
(a)



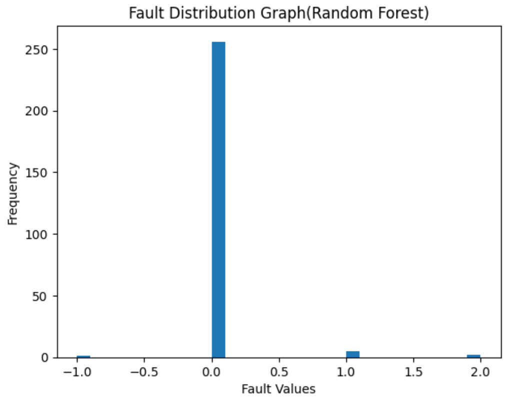
(b)



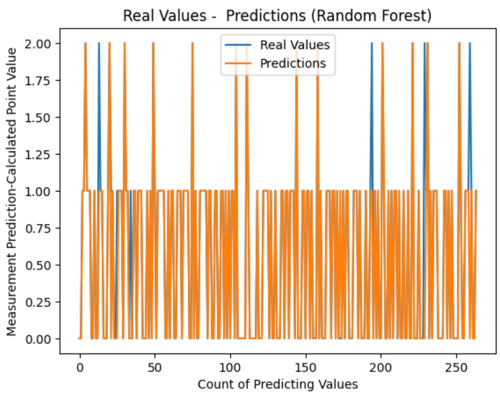
(c)



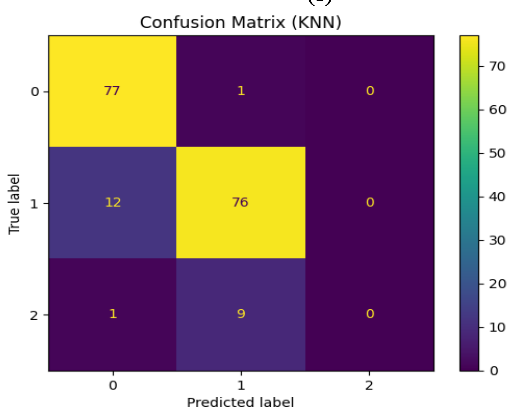
(d)



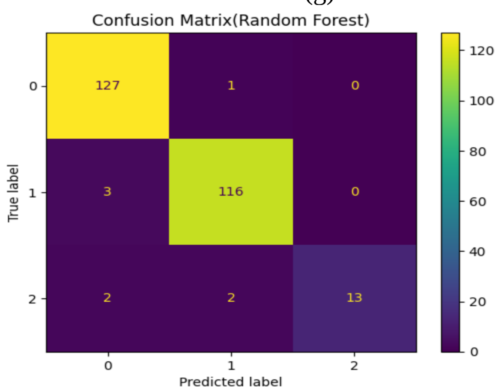
(e)



(f)



(g)



(h)

Figure 5. KNN and RF models training results (a. KNN Prediction Graph, b. KNN Error Distribution Graph, c. KNN Prediction Accuracy Graph, d. RF Prediction Graph, e. RF Error Distribution Graph, f. RF Prediction Accuracy Graph, g. KNN Confusion Matrix Graph, h. RF Confusion Matrix Graph)

The confusion matrix in Figure 5(g) indicates that the KNN model performs reasonably well but not perfectly. The matrix shows the number of true and predicted labels, where rows indicate true labels and columns indicate predicted labels. The KNN classifier showed strong performance in identifying instances in class 0, moderate performance for class 1, and failed to correctly classify any instance in class 2. This misclassification pattern highlights a difficulty with class 2, which may indicate that the model is unable to effectively discriminate this class.

The provided confusion matrix in Figure 5(h) shows the performance of the Random Forest classifier in three categories (0, 1 and 2). Each row corresponds to the actual class labels, while each column shows the predicted labels made by the model. The values in the matrix represent the number of instances classified under each predicted label. The Random Forest model performs robustly in discriminating between classes 0 and 1 with relatively few misclassifications. However, the classification accuracy for class 2 is slightly reduced, indicating that the model faces difficulties in distinguishing this class from the others.

The feature importance analysis revealed that certain soil properties significantly contributed to the fertility classification. The use of Mean Decrease in Impurity (MDI) measures allowed for the identification of key features, such as nutrient levels, pH, and organic matter content, which were crucial in predicting soil fertility. This underscores the importance of targeted soil management practices to enhance these critical parameters.

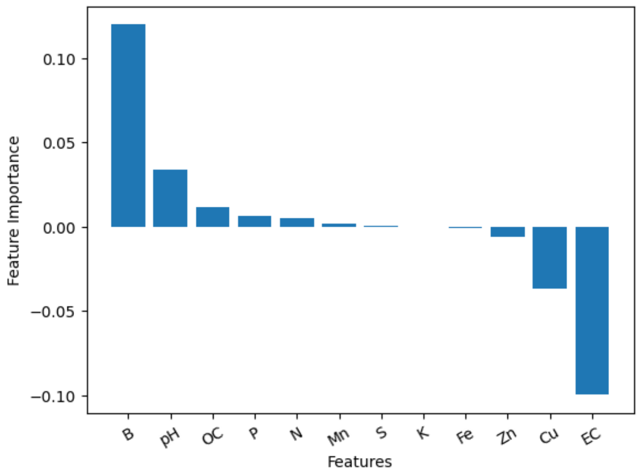


Figure 6. Feature Importance Graph

Figure 6 suggests that Boron (B) is the most influential feature in the model, significantly contributing to the predictions. In contrast, Electrical Conductivity (EC) has the least importance and may even negatively impact the model's performance. Features like pH and Organic Carbon (OC) also play crucial roles but to a lesser extent than Boron.

It is essential to consider these importance scores when making decisions about feature selection or further model tuning. Features with low or negative importance might be candidates for removal to simplify the model and potentially improve its performance. Conversely, ensuring the most important features are accurately measured and included in the model is critical for maintaining its predictive accuracy.

4. DISCUSSION AND CONCLUSIONS

The study demonstrates the potential of machine learning algorithms, in particular the Extra Trees and Random Forest models, to accurately predict soil fertility. The high accuracy achieved by these models underlines their robustness and reliability in performing soil fertility classification tasks. Furthermore, trait importance analysis provides valuable information for improving soil management practices by highlighting critical soil properties that influence fertility. The integration of advanced machine learning techniques with soil fertility assessment offers a promising approach for sustainable agriculture. By leveraging these technologies, farmers and agronomists can make informed decisions on crop selection and soil management, ultimately increasing agricultural productivity and sustainability. Future research should focus on expanding the dataset and exploring the application of these models in different agro-ecological zones to further validate their effectiveness and adaptability.

In conclusion, the application of machine learning models in soil fertility assessment offers a powerful tool for optimizing agricultural practices and ensuring long-term soil health. The findings from this study contribute to the growing body of knowledge on precision agriculture and highlight the importance of integrating technology with traditional agricultural practices to ensure sustainable food security.

Ethics Committee Approval
N/A

Peer-review
Externally peer-reviewed.

Author Contributions
Conceptualisation: A.A., E.A.; Research: A.A., E.A.; Materials and Methodology: A.A., E.A.; Supervision: A.A., E.A.; Visualisation: A.A., E.A.; Writing-Original Draft: A.A., E.A.; Manuscript-review and editing: A.A., E.A.; Other: All authors have read and accepted the published version of the article.

Conflict of Interest
The authors have no conflicts of interest to declare.

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