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RESEARCH

Assessment of soil classification using soft computing approaches for Erenler (Afyonkarahisar) region

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Abstract
The Casagrande chart is traditionally used for determining soil classes. However, processing samples individually on this chart is time-consuming, and human error, particularly at the classification boundaries, can lead to incorrect soil classification. To address these issues, this study employs machine learning algorithms to classify different soil types more efficiently and accurately. The primary goal is to integrate machine learning into engineering geology studies, leveraging technological advancements. As part of the study, field and experimental work was conducted, beginning with the collection of 272 soil samples from the designated study area to represent the entire region. The initial physical properties of these samples were then determined. The soil samples were carefully double-bagged and transported to the laboratory to prevent any degradation. Upon arrival, the water content of the samples was determined first. Subsequently, sieve analysis, consistency limits, and specific gravity tests were conducted in sequence. For the classification of soil types, machine learning methods, including Decision Tree (DT), Support Vector Machines (SVM), K-Nearest Neighbor (k-NN), and Artificial Neural Networks (ANN), were employed. Among these, the DT model demonstrated the highest performance, achieving a success rate of 91.5% across five different soil classifications. The ANN, SVM, and k-NN models followed, with success rates of 89.0%, 89.0%, and 86.0%, respectively. In addition, the hyperparameter optimisation of the models used in the study was provided and the minimum classification error analysis was presented. This study significantly contributes to the effective and efficient analysis of experimental data, demonstrating that soil classification can be successfully performed by integrating machine learning methods with numerical data.

Keywords Soil classification · Machine learning · Decision tree · Afyonkarahisar

Introduction

Soil classification systems are fundamental input parameters for understanding soil behavior under various climatic conditions, such as precipitation, wind, and temperature, as well as geological factors like tectonism, alteration, groundwater status, and mineralogical structure. These systems are crucial in the design of engineering projects, as the physical and mechanical properties of soil, particularly in such projects, heavily depend on accurate soil classification. Another significant reason for their importance is that they provide preliminary information to the project engineer about the mechanical properties of soils. When soil class is determined incompletely or incorrectly, a chain of errors can result, leading to a flawed project foundation and, consequently, an unsound project. Given the critical nature of soil classification, numerous systems have been developed by researchers. These systems generally involve determining grain size distribution, liquid limit, plastic limit, and plasticity index in the laboratory and analyzing the correlations between them (AASHTO, 1929; Casagrande 1948; American Society for Testing and Materials 2004; TSE, 2006a, 2006b). The primary difference among these systems lies

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in the varying percentages they define based on the material passing through the sieves. All of these measurements involve a laborious process of transporting field samples to the laboratory and interpreting the experimental results from the corresponding charts.

Soil classification systems have become increasingly important, particularly since the 2000s. These systems are widely utilized in various engineering fields, including the placement of structures on the ground, agricultural practices, and forestry studies (Gambill et al. 2016). They also play a crucial role in agricultural engineering, influencing soil classification improvements, erosion control, drainage properties, and irrigation strategies. The organic matter content of soil, which varies according to its clay, sand, gravel, and silt content, is a key factor in determining agricultural productivity and predicting soil behavior in engineering contexts (Barman and Choudhury 2020). Similarly, the application of artificial intelligence (AI) in agriculture is expanding rapidly. Traditional methods of soil analysis, which involve collecting samples, transporting them to a laboratory, and conducting experiments, are both costly and time-consuming. To address this, researchers have employed high-resolution cameras to capture images from different parts of a field, allowing them to classify soil types such as clay, gravel, and sand based on visual data. Some studies have focused specifically on using AI to determine grain size (Azizi et al. 2020; Alirezazadeh et al. 2021), achieving high accuracy rates (Azizi et al. 2020; Samadi and Samadi 2022). However, a significant drawback of these methods is the difficulty in accurately detecting silt content (Inazumi et al. 2020). Additionally, the mixed composition of soil types in the field, such as silty sand, sandy silt, or clayey sand, can undermine the reliability of these accuracy rates.

Some researchers have explored the use of machine learning to determine soil classes based on data obtained from cone penetration tests (CPT), standard penetration tests (SPT), the California bearing ratio (CBR) and tunneling, instead of relying solely on physical tests. These studies have demonstrated that soil classification accuracy can reach 90% or higher (Carvalho and Ribeiro, 2021; Khatti and Grover 2021b; Wu et al. 2021; Chala and Ray 2023).

In addition to physical experiments, studies in various areas of engineering are also conducted to assess rock quality. These include the prediction of triaxial compressive strength, uniaxial compressive strength and in-situ plate bearing tests using artificial intelligence. (Wang 2016; Khatti and Grover 2022b, 2024; Mao et al. 2023b, 2024).

The physical properties of soil are crucial in engineering, particularly regarding bearing capacity and the treatment of problematic soils. The coarse or fine grain size and the angularity or roundness of the gravels within the soil are especially important. Excessive fine grains can make the compaction process inefficient, increasing the risk of liquefaction, which can lead to significant issues in engineering structures. Similarly, rounded gravel complicates compaction efforts, necessitating more costly soil improvement methods. The liquid and plastic limits of soils also play a critical role in determining bearing capacity, assessing liquefaction risk, and selecting improvement methods, all of which directly impact the cost of engineering projects (Hoek 2006; Hoek and Bray 2009; Genç 2011; Wu et al. 2018; Azarafza et al. 2021; Mao et al. 2024). In addition, many studies utilize artificial intelligence techniques across various branches of engineering to determine shear strength in mine blasting, assess soil bearing capacity, and evaluate soil permeability (Khatti and Grover 2021d, 2023; Rabbani et al. 2022, 2023a, b, c; Hosseini et al. 2023; Mao et al. 2023a; Nanehkaran et al. 2023; Khatti et al. 2024; Rabbani et al. 2024a, b).

In agriculture, the grain structure of soil significantly impacts the germination and development of crops, ultimately affecting yield (Aksoy 2023b). For instance, soils with coarse-grained components like gravel and sand promote aeration and efficient irrigation, while fine-grained clay and silt create an impermeable layer that hinders soil aeration and groundwater absorption. During soil cultivation, coarse and angular pebbles pose challenges, whereas fine sand and rounded, smaller pebbles make the process easier. Additionally, soil pH is a crucial factor influencing the type of crops that can be planted and the yield that can be achieved. AI can assist in determining the soil's grain distribution, organic matter content, and pH. Other key parameters affecting soil fertility include moisture content, electrical conductivity, and the levels of phosphorus and potassium. Assessing these parameters in the field often involves lengthy and costly processes. To streamline soil fertility assessment and classification, researchers have employed AI to analyze various parameters (Holtz et al. 2011, 2015; Kalkan 2011; Rao et al. 2011; Mishra et al. 2012; Duchicela et al. 2013; Chaplot and Cooper 2015; Shahbaz et al. 2017; Radhika and Latha 2019; Alirezazadeh et al. 2021; Khatti and Grover 2021a; Jangir et al. 2022). Soil containing both coarse and fine-grained gravel, known as aggregate, plays a crucial role in retaining organic carbon, regulating organic matter content, and enhancing the soil's capacity to retain polyvalent cations due to its water-holding capacity. These factors contribute to the mineral content of the soil, which, in turn, helps boost yield, particularly in agricultural lands (Chaplot and Cooper 2015; Rahmati et al. 2017; Xiao et al. 2017; Haghverdi et al. 2018; Rivera and Bonilla 2020).

"Depending on the factors described in the above paragraphs, the importance of soil classification is increasing day by day. Today, the methods used for soil classification include both field and laboratory studies. As mentioned before, these methods are both time-consuming and costly. With current artificial intelligence applications, soil class can be determined by processing only the data obtained from image processing and laboratory or field studies, without the need to take samples from the field. However, intermediate soil classes cannot be accurately determined in analyses performed solely with image processing techniques without field sampling, which may increase the margin of error in the analysis (Sitton et al. 2017; Wu et al. 2018; Shi et al. 2018; Shekofteh and Masoudi 2019; Hanandeh et al. 2020; Eyo and Abbey 2021; Khatti and Grover 2021d, 2022a).

For the reasons explained above, this study determined soil classes by conducting laboratory tests on samples taken from the field. A total of 272 samples were analyzed using artificial intelligence, and the accuracy of the results was examined. This study suggests that the application of artificial intelligence in engineering geology could be beneficial. This article attempts to determine soil classes by considering the physical properties of soils, including liquid limit (LL), plastic limit (PL), plasticity index (PI), grain size distribution, and specific gravity. Soil classification was performed using machine learning methods. The data obtained from the study area were converted into numerical values after laboratory experiments and then classified using DT, SVM, k-NN, and ANN machine learning methods. Among these, the DT model was observed to have the highest classification success rate.

The remaining sections of this study are organized as follows. The second section presents the materials and methodology, detailing the application area of study, the experimental process, and the machine learning models used. The third section discusses the result of both the experimental study and the machine learning methods. The fourth section provides a discussion of the findings and offers conclusions. Finally, the fifth section concludes the study and highlights potential directions for future search.

Unlike the previous studies, the primary objective of this research is to ease the identification of soil classes through machine learning techniques. The study uses parameters such as clay, sand, gravel, and silt percentages, along with liquid and plastic limit values, plasticity index, and specific gravity as input data. A notable contribution to the literature is that no prior research on this topic has been conducted in the region where this study was performed. Additionally, this research aims to determine which machine learning technique performs most efficiently.

The rest of this study is organized as follows: The second section presents the material and method. In this section, the study area, the physical testing methods on the dataset, the data pre-processing process and the machine learning methods are described in detail. The third section presents the research findings and results. The fourth section provides a discussion on the results. The last section presents the general conclusion of the study.

Material and method

This section presents the materials and methods part of the study. For this purpose, the general flow diagram of the study is given in Fig. 1.

Figure 1 shows the flow diagram of the study under two headings. The first one is the data collection process and the other one is the classification process. Data collection process consists of preparatory work, field studies and laboratory studies. Classification process consists of machine

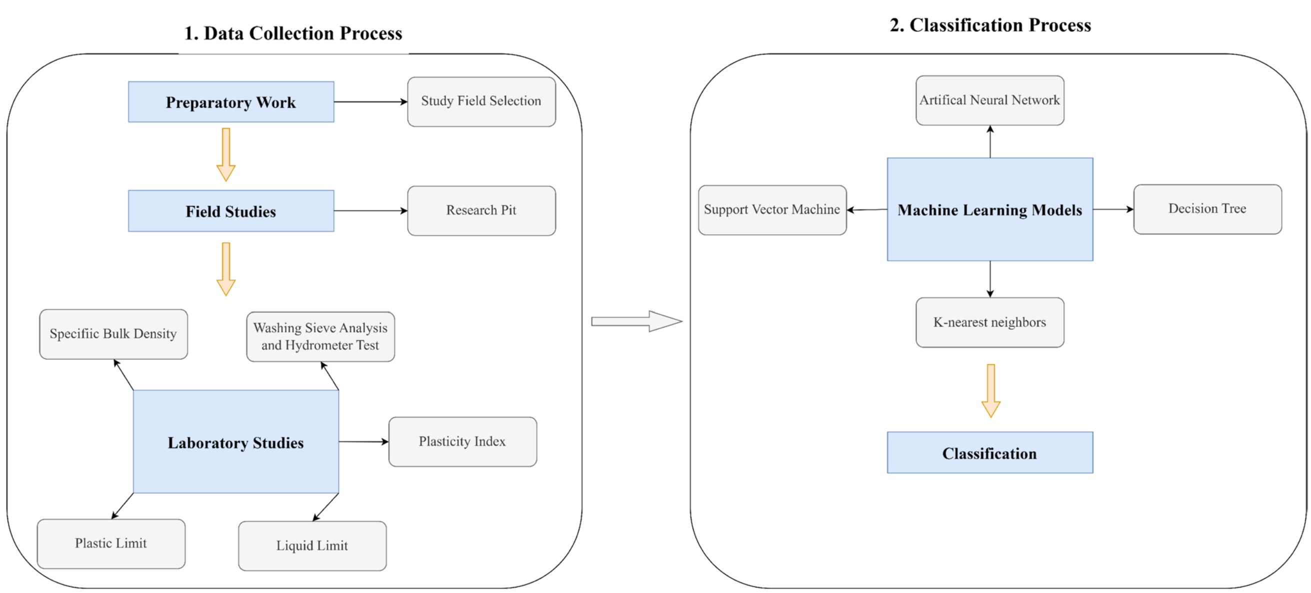


Fig. 1 Flow diagram of the study

learning models and classification. CorelDraw X8 was used to draw the geological map, while ArcGIS 10.1 was utilized for the location map. All other tasks were completed using Microsoft Office 2016.

Study area

Erenler Neighborhood and its immediate surroundings, located 10 km north of Afyonkarahisar province, form the core of the study area (Fig. 2). The region is characterized by plains interspersed with volcanic mountainous areas. Afyonkarahisar province and its surroundings experience a continental climate, with hot, dry summers and cold, rainy winters and springs. According to Uray et al. (2019), based on the Thornthwaite climate classification, Afyonkarahisar falls within the 1st degree mesothermal climate category, indicating a lack of excess water (Thornthwaite 1948).

In the city center, where there is a significant annual temperature variation, the lowest recorded temperature was −4.5 °C, and the highest was 29.6 °C. The average annual precipitation in the city center is 443.5 mm, with the lowest monthly precipitation recorded at 13.5 mm and the highest at 54.9 mm (General Directorate of Meteorology, 2021).

In summary, the study area is located within the Afyon basin, part of the western segment of the Afyon-Akşehir Graben Line, an active depression basin characterized by high annual temperature variations, significant precipitation, and edges controlled by major faults (Özkaymak and Sözbilir 2020).

Regional Geology

The study area is centered on the Quaternary-aged modern basin fill, located approximately 10 km north of Afyonkarahisar province. The underlying unit, referred to as "Afyon Metamorphites," dates back to the Paleozoic era and consists primarily of schists and marbles. The schists generally include chlorite-muscovite-albite-quartz and biotite varieties, often containing quartz veins. This brown, gray, and green unit exhibits a granoblastic texture (Yıldız et al. 2010; Kibici et al. 2012). In this tectonically active region, the marbles, which occasionally display a

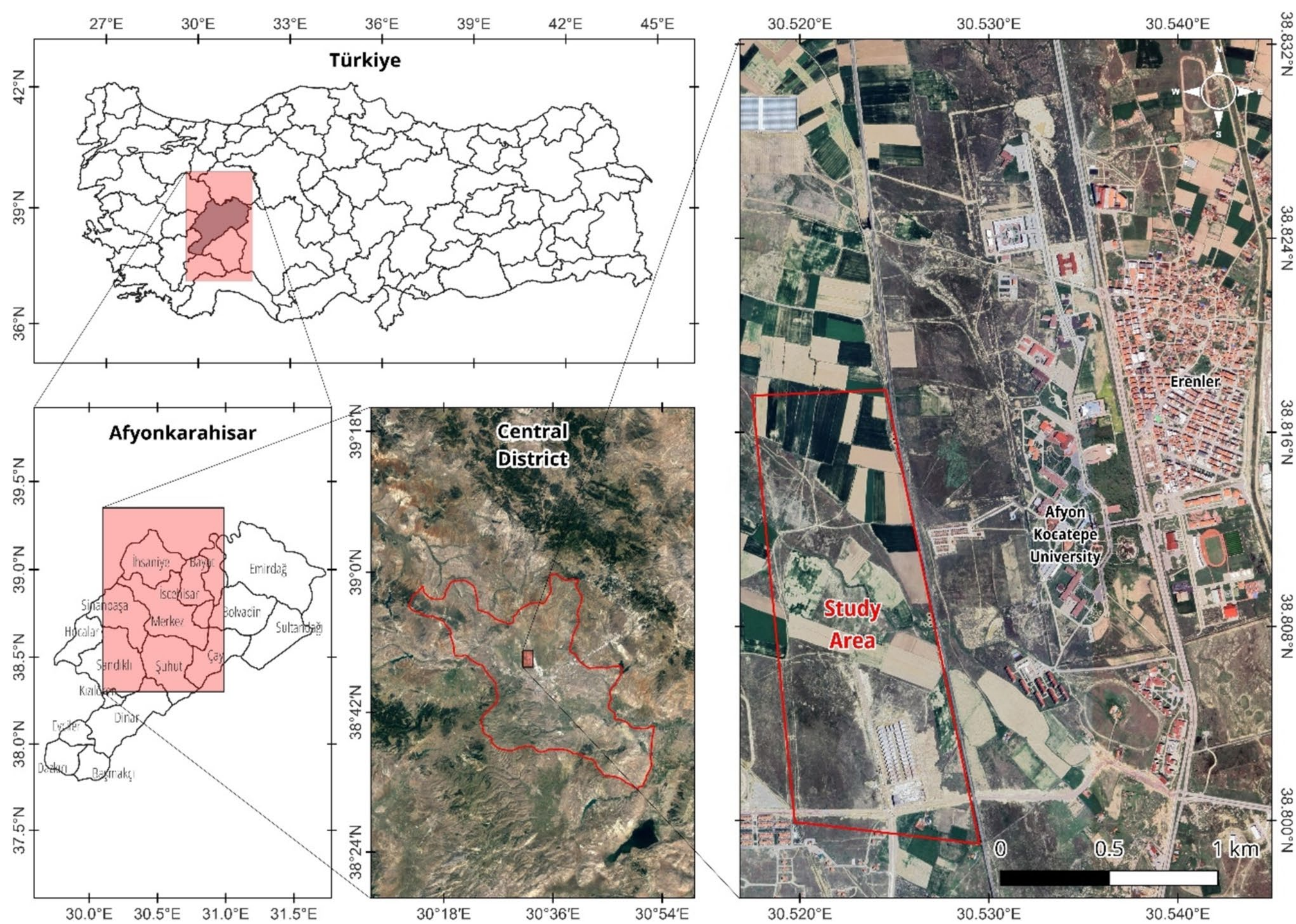


Fig. 2 Location map of the study area

brecciated structure due to tectonism, are primarily composed of calcite minerals. Secondary minerals such as quartz, chlorite, and sericite are observed to fill microcracks (Yıldız et al. 2010).

The Middle-Upper Miocene-aged Ömer-Gecek formation unconformably overlies the Afyon Metamorphites. Above this formation lies the Upper Miocene-aged Erkmen volcanites, the final product of regional volcanism. First named by Harut (1995), this unit consists of agglomerated pyroclastic rocks and lava flows. The gray and dark gray volcanites are trachytic in composition (Yıldız et al. 2010). The Quaternary-aged modern basin fill represents the youngest unit within the study area (Fig. 3).

Physical test methods

Along with the preparation of the 1/10,000 scale geological map in the study area, a grid map was prepared in order to work more systematically in the field. A total of 57 exploration pits with depths ranging from 0.5 m to 2.5 m were dug according to the grid map. Samples were collected at every half meter within these pits, and initial physical identification was performed on-site. To preserve their original physical properties, the samples were double-bagged and transported to the laboratory on the same day. The physical tests in the laboratory were conducted following the conditions outlined by the Turkish Standards Institute (2006a). In

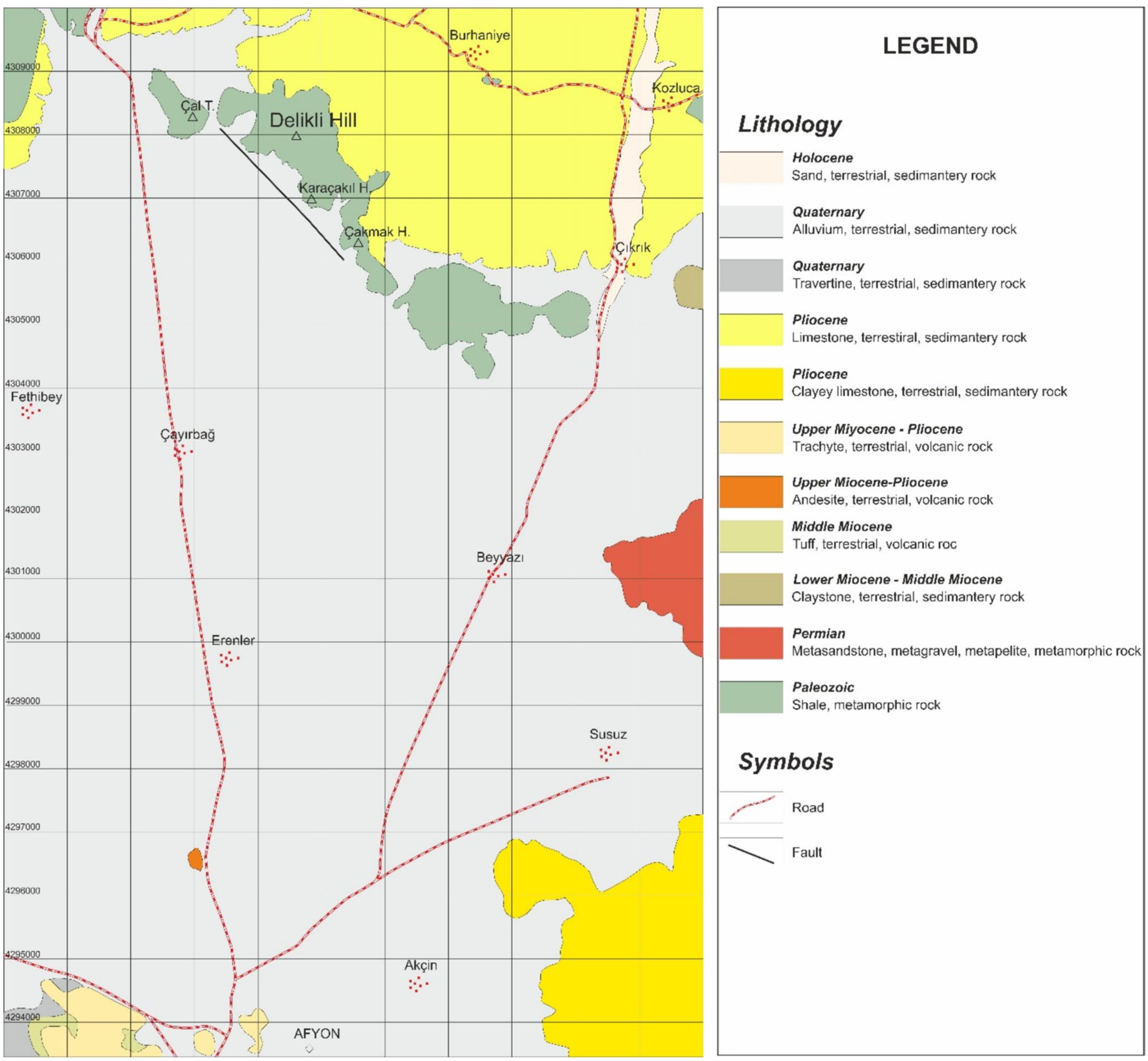


Fig. 3 1/25,000 scale geological map of the study area

this study, percentages of clay, silt, sand, and gravel, along with liquid limit, plastic limit, plasticity index, and specific gravity values, were used as input parameters, while soil classes with double symbols such as low plasticity clay-silt (CL-ML), low plasticity clay (CL), fat clay (CH), elastic silt (MH), and silt (ML) were used as output parameters (Table 1).

To determine the fine grain size, a hydrometer test was conducted in conjunction with a wash sieve analysis. During the wash sieve analysis, at least 200 g of material was washed on the sieve using water, with plastic waterproof containers placed underneath to prevent sample loss. After drying at room temperature, the samples were soaked in a sodium hexametaphosphate solution for 24 h to prevent clumping. A mechanical mixer was then used to ensure homogeneous distribution of grains within the samples. In the final step, the samples were transferred to a 1000 ml graduated cylinder, and the remaining volume was filled with distilled water. The prepared solution was measured with a hydrometer at intervals of 30 s, 1, 2, 4, 8, 15, and 30 min, as well as 1, 2, 4, 8, and 24 h (Fig. 4) (TSE 2006a, 2006b).

For the liquid limit test, the powdered samples were placed in a porcelain dish using a spatula, and the water content was gradually increased. The first weighing of the empty porcelain dish was recorded. Once the sample reached the desired consistency, it was placed in the Casagrande apparatus, and a groove was cut from the center using a grooving tool. The crank handle was turned until the groove closed, and the number of drops was recorded. A sample was taken from the center of the groove, placed in an oven at 105 °C for 24 h, and weighed to determine the liquid limit value

Table 1 Statistical values of the physical properties of the inlet parameters in the study area

Description		Minimum	Maximum	Average
Input	Clay (%)	51.00	98.00	87.00
	Silt (%)	0.00	25.00	2.00
	Sand (%)	1.00	48.00	11.00
	Gravel (%)	0.00	4.00	0.00
	Liquid Limit (%)	25.00	75.00	53.00
	Plastic Limit (%)	15.00	37.00	28.00
	Plasticity Index (%)	3.00	49.00	23.50
	^{3}Specific Gravity (gr/cm)	1.67	2.98	2.22
Output	Soil Class	0: CL-ML, 1: CL, 2:CH, 3: MH, 4: ML		

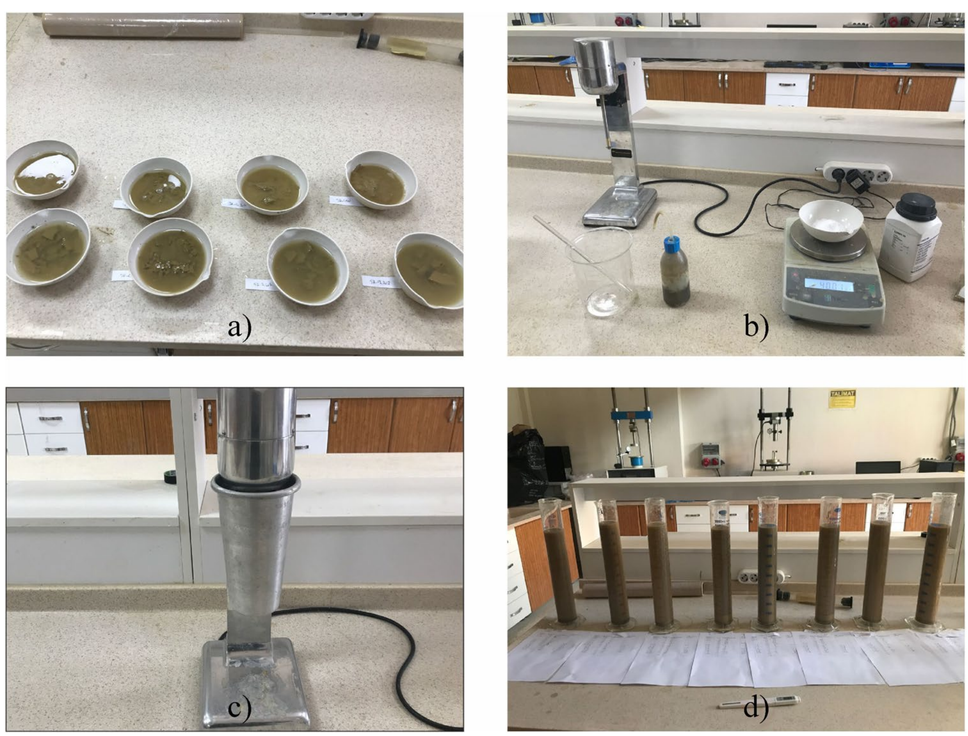


Fig. 4 (**a**) Soaking of samples in sodium meta hexaphosphate solution, (**b**) Hydrometer test equipment, (**c**) Mechanical stirrer for homogeneous distribution of samples, (**d**) Reading from the prepared solution

(Fig. 5). For the plastic limit test, 20 g of the sample was rolled on a glass plate by hand until it reached a diameter of 3 mm. The process was continued until cracks and ruptures appeared in the 3 mm sample. Finally, the entire sample was dried in an oven at 105 °C for 24 h, weighed, and the plastic limit value was determined (Fig. 6) (TSE 2006a, 2006b).

50 ml pycnometers were used during the experiment. At first, the raw weights of the pycnometers were weighed and recorded in the experiment sheet. Then the pycnometer was filled with water and weighed. Again, the pycnometer was dried and filled with some sample, at least 20 g of sample. The remaining part was filled with water and the final weight was weighed and the calculation was started (TSE 2006a, 2006b).

Data pre-processing

Nowadays, data is collected automatically by sensors and other electronic devices, as well as being recorded manually. This data needs to be pre-processed so that it can be analysed correctly and can be easily utilised by users. Data mining, machine learning and AI techniques require data pre-processing to deal with corrupted data. This process helps to improve the quality of the data, extract meaningful

Fig. 5 (**a**) Placing the sample in the porcelain crucible, (**b**) Hollowing out, (**c**) Sampling from the center, (**d**) Weighing

Fig. 6 (**a**) Thinning the specimen to 3 mm diameter, (**b**) Cracks are seen, (**c**) Making the specimen whole, (**d**) Weighing

and learnable features, and provide a clearer interpretation of the results obtained. The steps of data pre-processing are as follows:

Data collection Data collection is the process of retrieving and recording data from their sources. Data are generated after the samples obtained from the research site were studied in the laboratory environment. Collecting information from data sources plays an important role in the process of creating a dataset. In order to obtain an appropriate and reliable dataset, it is essential that the data are collected and recorded correctly.

Data cleaning Data cleaning involves correcting errors, missing or incorrect data, identifying outliers and removing unnecessary information. This step plays an important role in improving the quality of the data set. For example, in a situation with missing data, these deficiencies can be filled with the mean or median. This process is necessary to ensure the consistency and accuracy of the data.

Fusion of data Data from different sources may need to be combined prior to model training. At this stage, data from various sources are integrated into a single dataset.

Data splitting Data splitting is the process of dividing the dataset into training, validation and testing sets. This step is necessary for training, validating and testing learning algorithms. In addition, data splitting helps to avoid problems such as overfitting. The data set is usually divided into training, validation and test sets.

In this study, the training and testing process was carried out using the k-fold cross-validation method (Hastie et al. 2009). K-fold cross-validation divides the dataset into k equal regions. Here, the division is chosen as $k = 10$ and the training-testing process is carried out. Each region is processed by creating test data one by one. The remaining 9 parts are used as training data. This process is repeated 10 times and each time a different part is selected as validation data. To evaluate the performance, the accuracy rates calculated in each cycle are averaged. The described method is given in Eq. 1.

$$Performance = \frac{1}{10}\sum_{i=1}^{10} Performance_i \tag{1}$$

Saving the data After the data pre-processing steps have been completed, the data is usually stored in a file or database. This step ensures that the data is safely stored for future data analysis or machine learning applications.

Machine learning methods

This section presents the four different machine learning methods used in the study: DT, SVM, k-NN, and ANN. The classification process was performed using MATLAB version 2022b.

Decision tree (DT) DT is a machine learning classification method structured as a tree, consisting of decision nodes and leaf nodes. The structure follows a top-down approach, where multiple algorithms are used to split a node into more than two sub-nodes.

Support vector machines (SVM) SVM is a popular machine learning method used in classification and regression tasks. It can classify binary or multiple classes by determining and drawing the most appropriate decision boundary, or gap, between the classes (Saygın et al. 2023).

k-Nearest neighbors (k-NN) This method is based on the relationship between a data point and its neighboring data points, which is determined by their distances. The “k” in k-NN refers to the number of nearest neighbors considered. Various distance metrics can be used to calculate this distance, such as Euclidean, Manhattan, or Minkowski (Cengiz et al. 2022).

Artificial neural networks (ANN) ANN is an algorithm inspired by the neural networks in the human brain. It involves input, output, and the error between them. The model adjusts the weights between input and output to minimize error, with the goal of processing inputs according to their importance (Aysal et al. 2023). This is done by selecting appropriate activation functions. An ANN may contain one or more hidden layers, each with a certain number of neurons, with no restriction on the number of neurons in these layers. Figure 7 illustrates the flow of an artificial neural network from input to output.

Figure 7 shows the process of x inputs to y outputs in the artificial neural network. Accordingly, it is seen that the m features in the input are multiplied by the weight coefficients w and summed in the sum symbol and then given to the activation function to obtain the output value.

Research findings

Physical experiment results

Specific gravity is defined as the ratio of the unit weight of a grain to the unit weight of water. Determining specific gravity provides important insights into the physical properties of soil samples. This experiment, which can be conducted on both coarse- and fine-grained soils, involved testing the specific gravity of 272 samples collected during the field study. According to the test results, the specific gravity of the samples ranged from a minimum of 1.67 g/cm³ to a maximum of 2.98 g/cm³, with an average value of 2.13 g/cm³. The calculation for a sample soil is shown in Table 2, and the specific gravity (Gp) calculation is provided in Eq. 2.

$$Gp = \frac{E}{(B - A) - (D - C)} \tag{2}$$

Wash sieve analysis and hydrometer tests on fine-grained soils were performed on all 272 samples. In these tests, the percentages of clay, silt, sand, and gravel were determined to assess the grain size distribution of the soil samples. The clay content of the 272 soil samples ranged from a minimum of 51% to a maximum of 98%. Most of the samples had an average clay content of 87%, indicating that the majority of the soil consists of clay. The negligible gravel content, found only in a few samples, suggests that nearly all of the region is composed of fine-grained soils. Regarding the remaining materials, silt content ranged between 0% and 25%, with an average of 2%. Sand content ranged from a minimum of 1% to a maximum of 48%,

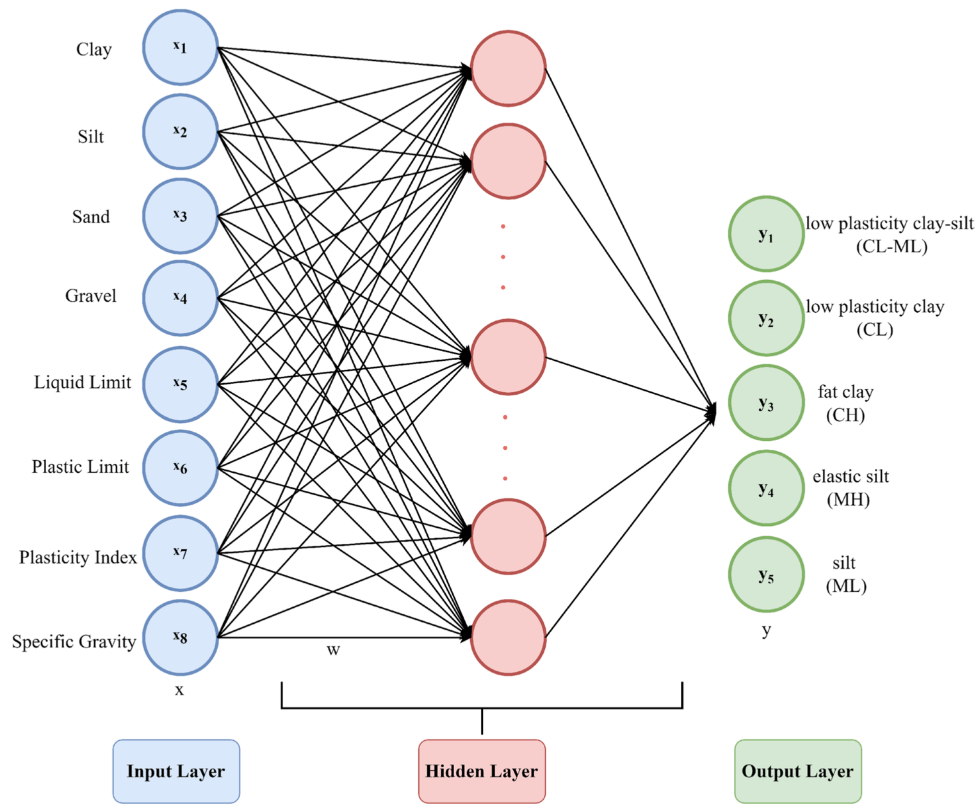


Fig. 7 Artificial neural network structure

with an average of 11%. This data indicates that the fine-grained soils in the region are primarily composed of clay, with some sand content. An example of the test results is shown in Fig. 8.

The consistency limit tests showed that liquid limit values ranged from 25 to 75%, with an average of 53%; plastic limit values ranged from 15 to 37%, with an average of 28%; and the plasticity index ranged from 3 to 49%, with an average of 23.5% (Table 1). Figure 9 presents a sample liquid limit graph, while Tables 3 and 4 provide sample calculations for the liquid limit and plastic limit used in the study.

Machine learning findings

This section presents the findings obtained from the classification process using machine learning methods. The performance of these methods is compared with the confusion matrix shown in Fig. 10.

The accuracy evaluation criterion was used to evaluate these methods. The evaluation criterion considered is given in Eq. 3.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{3}$$

Accuracy score is a key metric used to evaluate the performance of predictive systems, such as classification models. It measures the prediction accuracy of the trained algorithm in practical applications. However, it is important to note that this metric is reliable only if the data samples used to train the algorithm accurately represent the range of situations that can occur in real-world conditions.

Accuracy values are calculated with the complexity matrices given in Fig. 11. The results calculated using Eq. 3 are given in Fig. 12.

Figure 12 shows the success rates obtained by four different algorithms for five distinct classes (CL-ML, CL, CH, MH, and ML) as well as for all classes in the dataset. When the results are analyzed class by class, it is evident that all classification models, except SVM, fail to correctly predict the CL-ML class. This issue arises due to the use of double symbols, which reflects the challenge in determining the exact soil class within the soil classification system.

Table 2 Specific gravity test sheet (sample SK-1,1a13)

Description	Symbol	Value
Pycnometer weight, (gr)	A	48.49
Pycnometer + water weight, (gr)	B	148.30
Pycnometer + Dry sample weight, (gr)	C	75.53
Pycnometer + Sample weight + water weight, (gr)	D	164.34
Dry sample weight, (gr)	E	27.04
Specific Gravity of the Sample	Gp	2.45

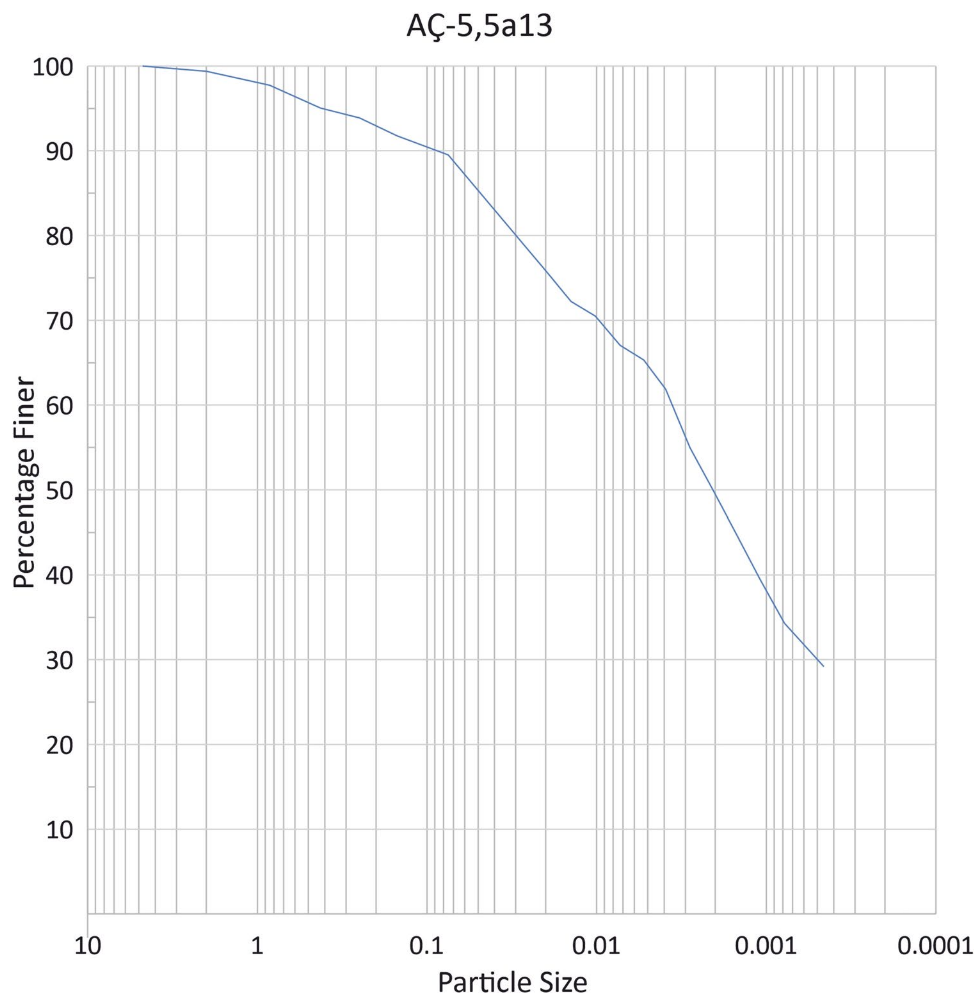


Fig. 8 Granulometer curve plotted according to the sieve analysis result (sample AÇ−5,5a13)

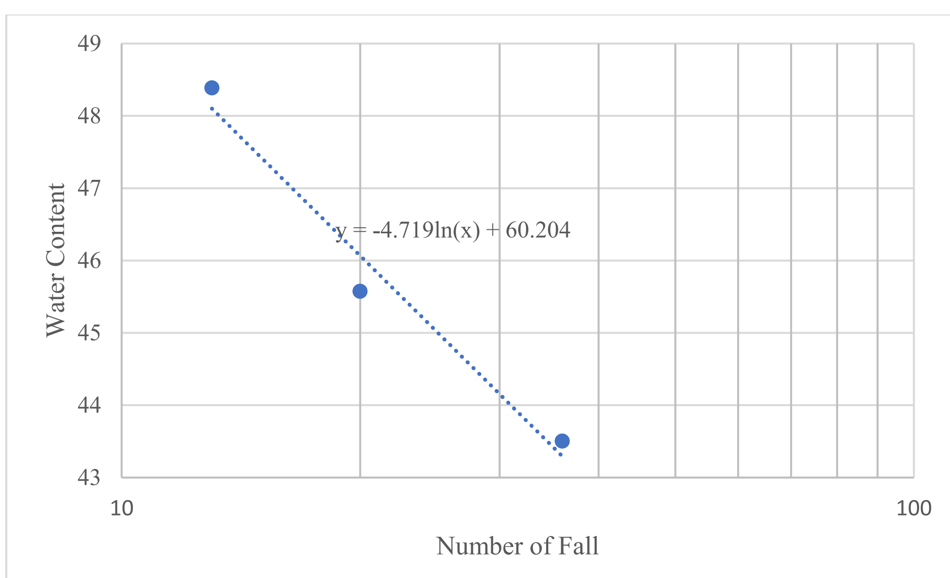


Fig. 9 Liquid limit test graph (sample AÇ−1,1a13)

Table 3 Liquid limit test sheet (sample AÇ−1,1a13)

Container weight (gr)	Container + Wet sample weight (gr)	Container + Dry sample weight (gr)	Number of falls	Water amount (gr)	Dry sample weight (gr)	Water content (%)
23.97	47.16	40.13	36.00	7.03	16.16	43.50
18.46	38.36	32.13	20.00	6.23	13.67	45.57
19.28	43.17	35.38	13.00	7.79	16.10	48.39

Table 4 Plastic limit test sheet (sample AÇ−1,1a13)

Container weight (gr)	Container + Wet sample weight (gr)	Container + Dry sample weight (gr)	Water amount (gr)	Dry sample weight (gr)	Water content (%)
24.44	33.15	31.62	1.53	7.18	21.31

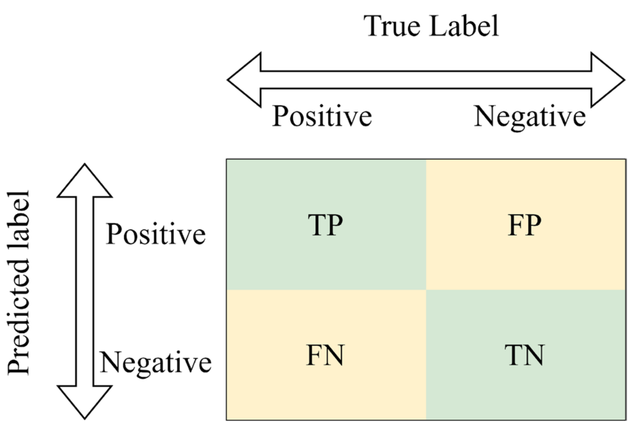


Fig. 10 Complexity matrix

For the CL and CH classes, the models achieved over 90% accuracy. In the MH and ML classes, the DT and ANN algorithms ranked first and second, respectively. The 'All' column summarizes the performance of the classification models across all classes, showing that the DT model achieved the highest success rate at 91.5%. Following this, the SVM and ANN models both achieved a success rate of 89%, while the k-NN algorithm reached 86%.

Another graphical tool used to assess the performance of a classification model is the ROC (Receiver operating characteristic) curve (Beguería 2006; Aksoy 2023a). The ROC curve shows the relationship between precision and accuracy as the threshold values change in binary classification systems. More precisely, the ROC curve shows the ratio of true positive rates to false positive rates. As a model's sensitivity increases, its specificity typically decreases, and vice versa. An ideal ROC curve passes through the upper left corner, indicating both high sensitivity and high specificity. The Area Under the Curve (AUC) represents the area beneath the ROC curve, with values ranging between 0 and 1. The closer the AUC value is to 1, the better the model's performance. High AUC values indicate strong model performance across different cut-off points, whereas low AUC values suggest poor model performance.

Figure 13 shows the ROC curves and AUC values for four different models. In the obtained curves, it is seen that the AUC values of k-NN and ANN models have high values except for the soil type with 0 class (CL-ML). This is due to the fact that the number of soil classes with double symbols is quite low and the classification is incorrect in k-NN and ANN models. DT and SVM models have high AUC values in all classes. This indicates that DT and SVM models perform well in general. Figure 14 shows the minimum classification error plot of the four classification models.

In Fig. 14, the optimum operating conditions of the classification models are investigated. Accordingly, minimum classification error graphs were obtained by optimising the hyperparameters for 30 iterations. Optimisation results are given at the top right of each figure. Here, when the model has finished tuning its hyperparameters, a model trained with the optimised hyperparameter values (Bestpoint hyperparameters) is returned.

Result and discussion

This section presents the results of this study and discusses related work in the literature. Table 5 was compiled based on a review of these studies. In Table 5, the references, parameters used, data collection methods, classification models, and performance metrics are listed in separate columns.

The studies summarized in Table 5 include current research on the topic. Barman and Choudhury (2020), Azizi et al. (2020), and Inazumi et al. (2020) utilized a method of obtaining images with the help of cameras in the field. These images were then processed using SVM and CNN algorithms through computer programs like Python and MATLAB to determine soil classes. These studies reported accuracy rates above 90% (Barman and Choudhury 2020; Azizi et al. 2020; Inazumi et al. 2020).

In another study, Gambill et al. (2016) attempted to estimate soil classes by downloading digital images of 35 states and 131 counties in the USA using USDA SSURGO data, achieving a 99.1% accuracy rate with the RF method.

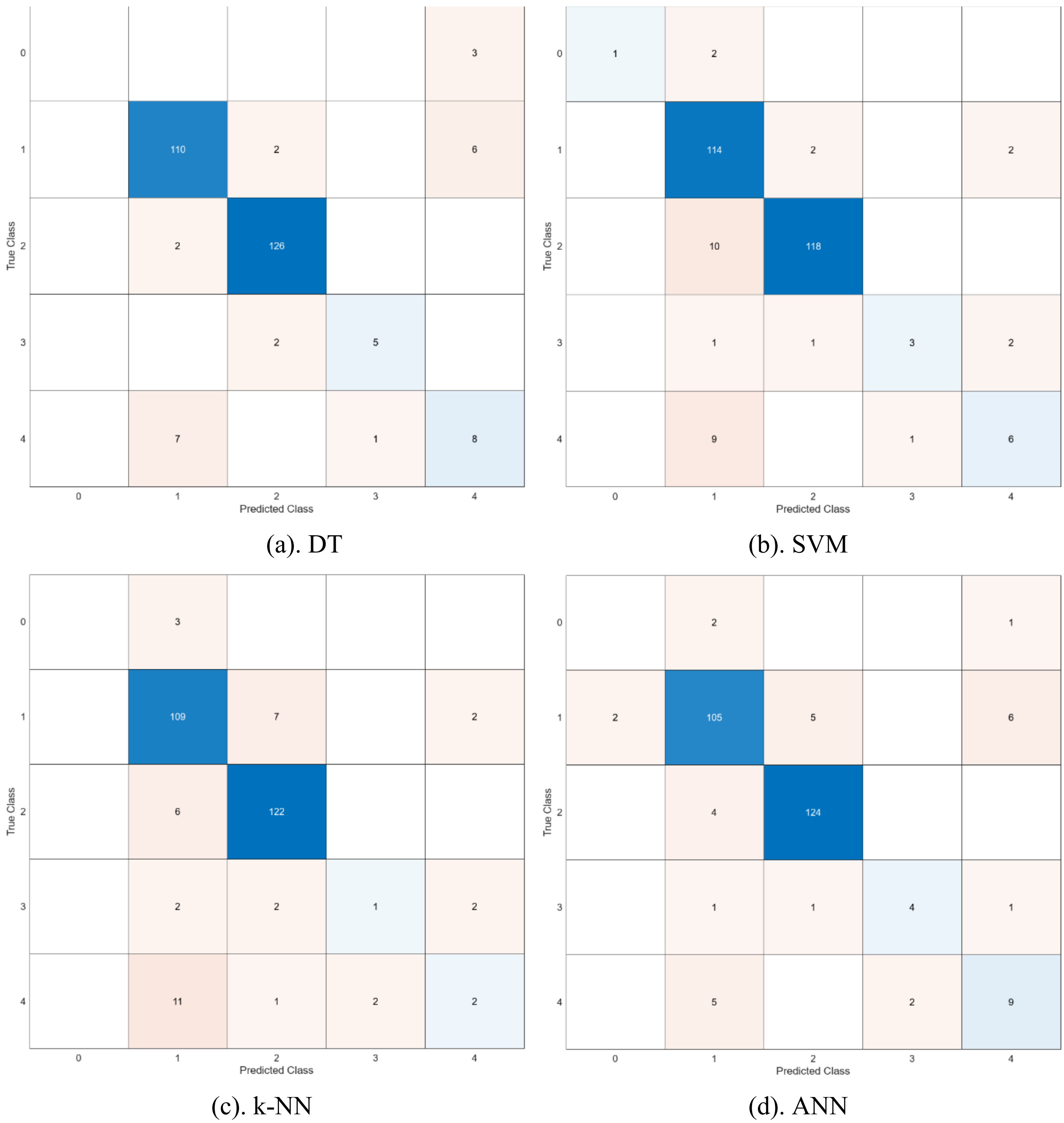


Fig. 11 Complexity matrices of four different classification methods

Similarly, Sitton et al. (2017), Wu et al. (2018), Shekofteh and Masoudi (2019), Hanandeh et al. (2020), Wu et al. (2021), and Chala and Ray (2023) collected data directly from the field. These studies analyzed the data obtained from field samples or experiments using artificial intelligence and various algorithms, with accuracy rates ranging between 85% and 99%.

Shi et al. (2018) used the Recursive Feature Elimination method, based solely on the amount of sand, silt, clay, and organic matter, and found that the accuracy rate ranged between 0.03 and 0.44. Rivera and Bonilla (2020) used ANN and GLM methods based on sand, silt, clay, pH, organic matter content, and water-stable aggregates, achieving accuracy rates of 0.82 and 0.63, respectively.

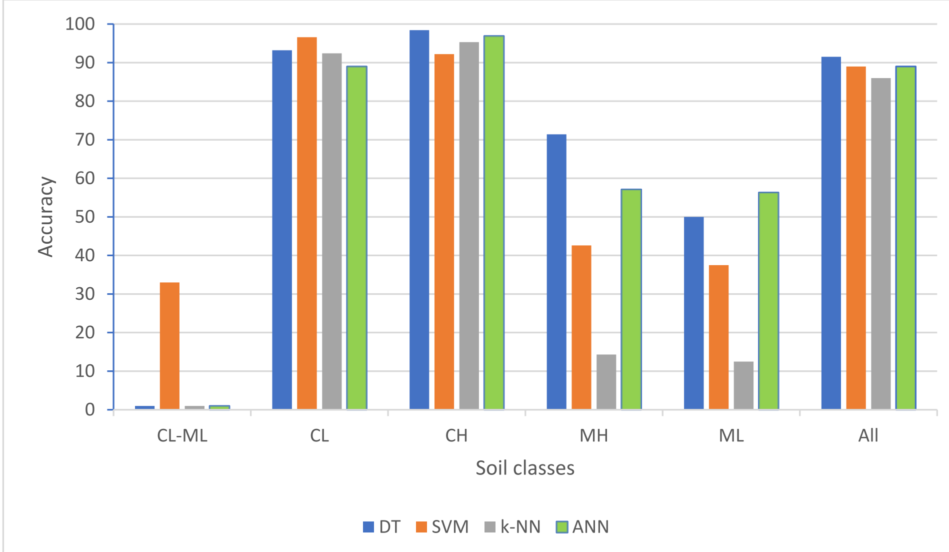


Fig. 12 Accuracy values of machine learning methods

Eyo and Abbey (2021) conducted a study based on cation exchange capacity, carbonate content, specific gravity, clay friction, and consistency limits, reporting accuracy rates of 0.68, 0.71, and 0.68 using LR, ANN, and DF methods, respectively.

In the above studies, it was observed that accuracy rates exceeded 90% in studies using only image processing. The main reason for this high accuracy is that the soil classes in the studied areas were visually distinguishable due to their large grain size. In other words, there was no need to differentiate between fine-grained sand and silt, only between coarse-grained and fine-grained soils. While distinguishing coarse and fine-grained soils is important, relying solely on this method may lead to errors when determining detailed soil classifications.

Additionally, the variation in accuracy rates in studies that collected data from the field can be attributed to the use of different parameters and algorithms in determining soil classes. In this study, physical properties of the soil, such as clay, sand, silt, gravel percentages, consistency limits, and specific gravity, were considered. The results showed a 91.5% success rate with the DT model. The primary reason for not achieving a 100% accuracy rate was the presence of samples with double symbol soil classes and the small number of such samples. Specifically, the artificial intelligence misclassified the CL-ML soil class by assigning it to the closest value. This issue was identified as a key area for improvement in AI. Despite these challenges, the study's results highlight the significance of this research. It is suggested that an optimal method could be determined by conducting a more comprehensive study that includes additional parameters and algorithms.

Conclusions

The study focuses on the classification of soil samples collected from the field using machine learning techniques. The results obtained from this research are presented below:

(i) *Laboratory Studies*: In the laboratory phase, specific gravity, sieve analysis, and consistency limit tests were conducted on 272 soil samples collected from the field. These tests were used to determine the physical properties of the soil samples. The analysis revealed the following average values: clay content at 87%, silt content at 2%, sand content at 11%, gravel content at less than 1%, liquid limit at 53%, plastic limit at 28%, plasticity index at 23.5%, and specific gravity at 2.22 g/cm^3. Based on these results, the soils were classified, with the predominant soil classes identified as oily clay (CH) and clean clay (CL). Additionally, small quantities of sandy elastic silt (MH) and silt and sand (ML) were also present. The CL-ML soil class, which is characterized by double symbols and is notoriously difficult to identify, was found to be quite rare.

(ii) *Classification Process*: The data obtained from the laboratory tests were digitized for further analysis. Using the 10-fold cross-validation method, the 272 digitized data points were classified using various machine learning methods. The classification process yielded success rates of 91.5% for the DT model, 89.0% for SVM, 86.0% for k-NN, and 89.0% for the ANN model. The DT model, which achieved the

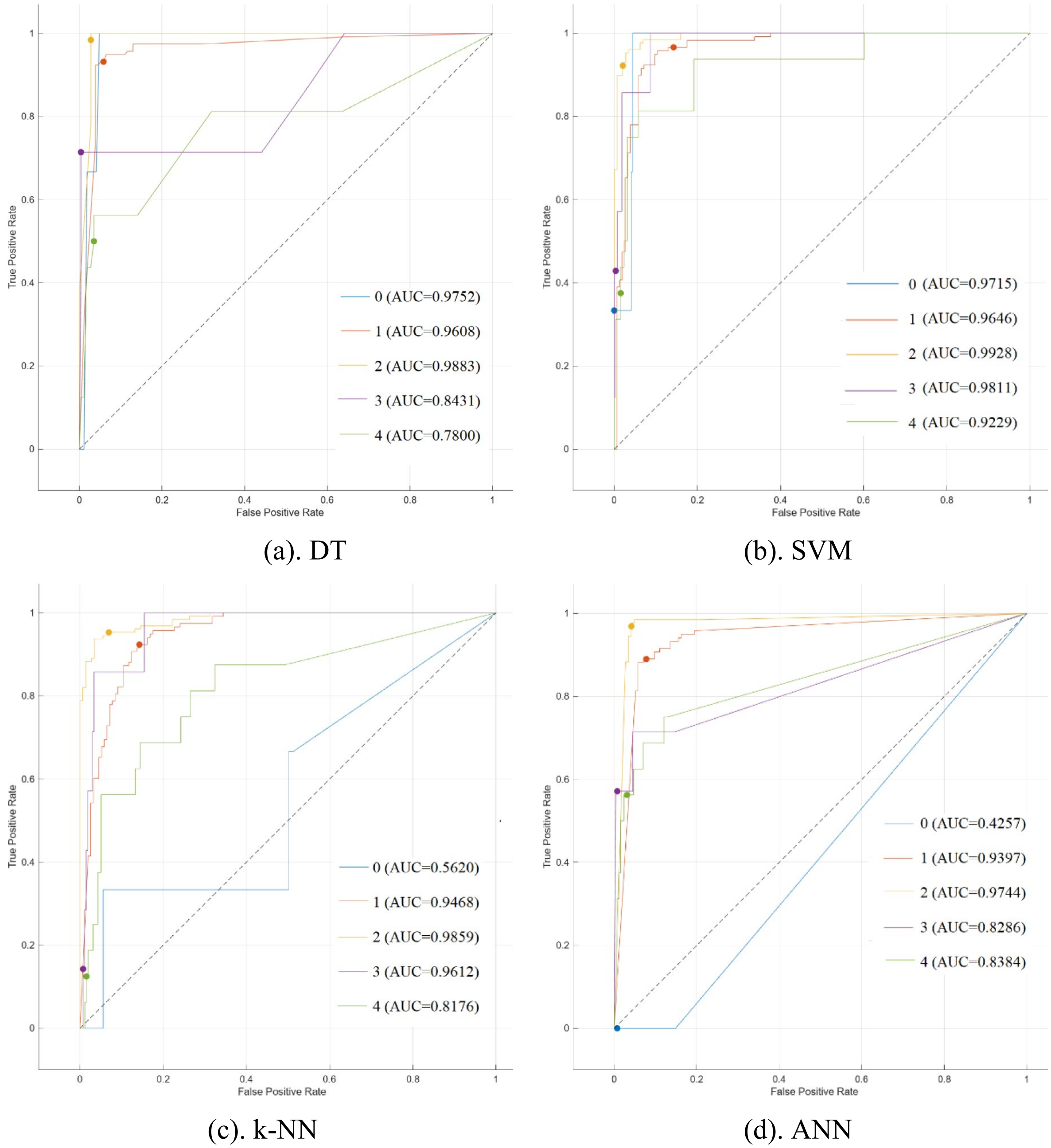
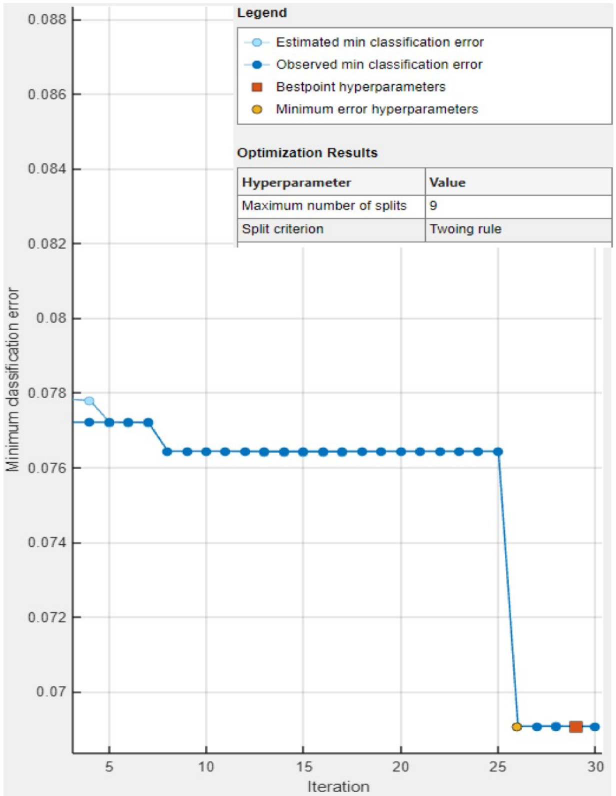


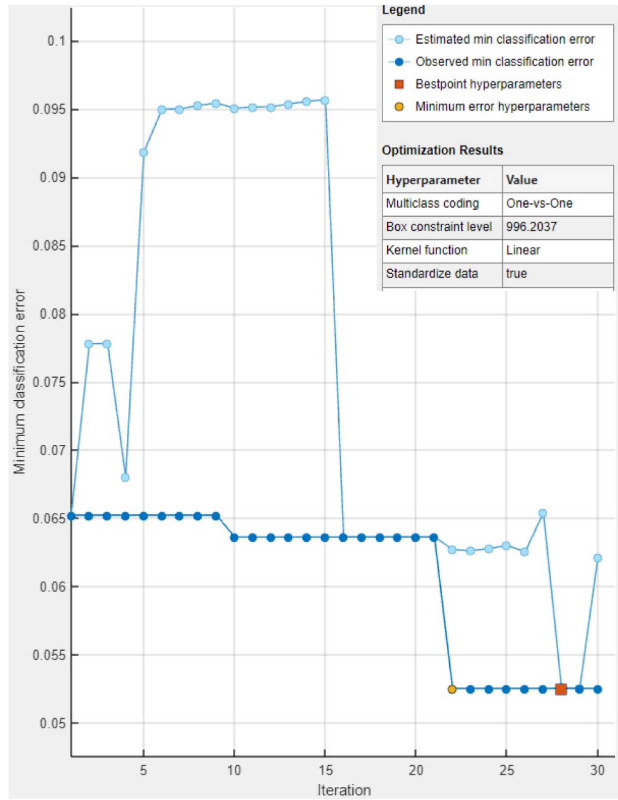
Fig. 13 ROC curve and AUC values obtained by four different classification models for all classes

highest classification success rate, outperformed the other machine learning models.

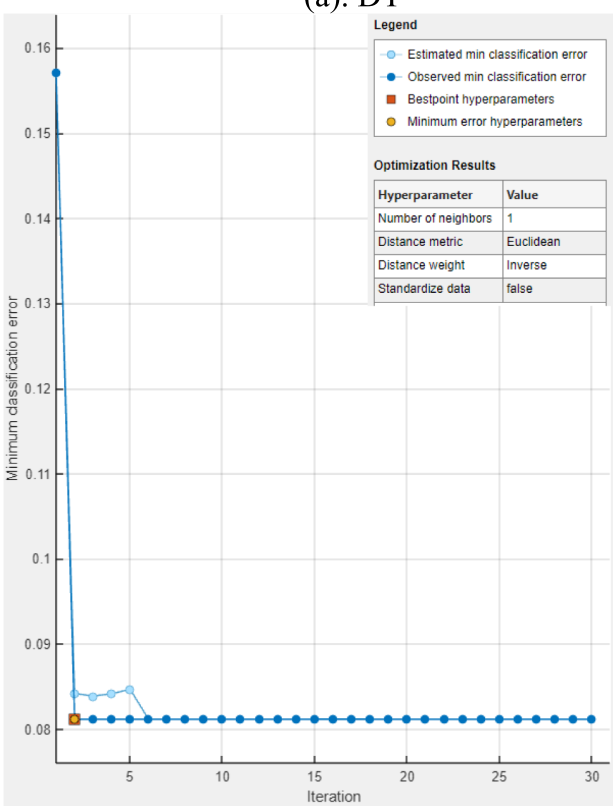
As a result, in this study, where field, laboratory, and office activities were conducted simultaneously, the soil classes in the Erenler neighborhood of Afyonkarahisar province were determined using machine learning techniques. Liquid limit, plastic limit, sieve analysis, and specific gravity tests, which also served as input parameters, were performed on 272 samples collected through field studies. It was found that the average clay content was 87%, gravel content was nearly 0%, silt content was 2%, and sand content was 11%. Additionally, the average plasticity index was 23.5%, and the average specific gravity was 2.22 g/cm³. These data were then analyzed using machine learning techniques such as DT, SVM, k-NN, and ANN. Among the methods, DT produced the best result with a success rate of 91.5%. The other models, ANN, SVM, and k-NN, yielded success rates of 89%, 89%, and 86%, respectively.



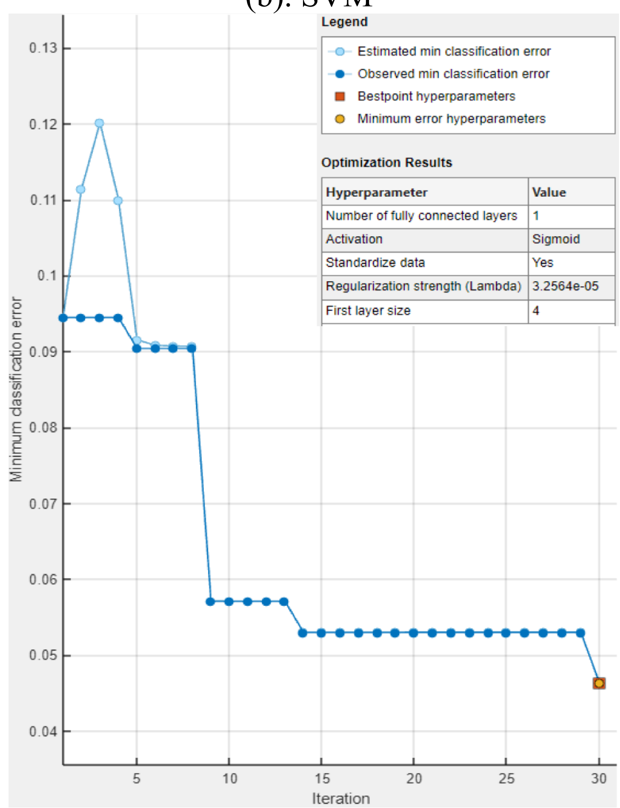
(a). DT



(b). SVM



(c). k-NN



(d). ANN

Fig. 14 Minimum classification error plot of classification models

Table 5 Consideration of studies in the literature

References	Parameters	Method of obtaining the data	Classification models	Performance criteria
Alirezazadeh et al. 2021	2030 × 1926 pixels 1401 × 1201 pixels 901 × 851 pixels	60 cm 80 cm 100 cm	CNN models VGG16, ResNet-50, MobileNetV2	*Accuracy* SoilNet 60 cm; 97.34% 80 cm; 97.04% 100 cm; 97.13%
Azizi et al. 2020	Two 10 megapixel cameras	Image processing 60 cm	CNN models VggNet16, ResNet50, Inception-v4	*Accuracy* VggNet16: 97.12 ResNet50: 98.72 Inception-v4: 95.83
Eyo and Abbey 2021	Cation Exchange capacity Carbonate content Specific surface area Clay friction Consistency limits	Data collection	LR ANN DF	*AUC Value* *VE Model 0.84* *SE Model 0.83*
Gambill et al. 2016	USDA SSURGO image dowload	Image processing	RF	*Accuracy* RF: 99.1
Hanandeh et al. 2020	Consistency limits Clay Moisture content Silt	Data collection	ANN GA	R^2 *values* ANN:0.9784 GA: 0.9725
Rivera and Bonilla 2020	Sand Silt Clay pH Organic matter content Water-stable aggregates	Data collection	ANN GLM	R^2 *values* ANN: 0.82 GLM: 0.63
Shekofteh and Masoudi 2019	Electrical conductivity Bulk density Particle density Cabonate calcium equivalent Soil organic matter pH Clay Silt Sand Porosity	Data collection	GA-ANN	R^2 *value* GA-ANN: 0.92
Shi et al. 2018	Sand Silt Clay Soil organic matter	Data collection	RFE	R^2 *values* Sand: between 0.05–0.13 Silt: between 0.03–0.17 Clay: between 0.03–0.29 Soil organic matter: between 0.06–0.35
Sitton et al. 2017	Pen test Stick test Shine test Test tube particle gradation The jar test Consistency limits Sieve Analyses	Data collection	CEB	*Accuracy* CEB: 85.00

Table 5 (continued)

References	Parameters	Method of obtaining the data	Classification models	Performance criteria
Wu et al. 2018	Elevation (m) Slope Slope length Slope height Stream power index Flow path lengtg Multiresolution of the ridge top flatness index Multiresolution of valley botto flatness index	Data collection	SVM	*AUC Value* 0.943
Wu et al. 2021	CPT Gravel Sand Silt	Data collection	RF	*AUC Value* Silt: 0.98 Sand: 0.98 Gravel: 0.99
Barman and Choudhury 2020	Android mobile 13 megapixel camera	Image processing	SVM	*Accuracy* SVM: 91.37
Chala and Ray 2023	CPT Depth Total vertical stress Unit weight Effective vertical stress Friction ratio	Data collection	ANN SVM RF DT	*Accuracy* SVM: 99.84 RF: 99.23 DT: 95.67 ANN: 98.82
Inazumi et al. 2020	56 × 56 pixel images 28 × 28 pixel images	Image processing	CNN	*F values* 0,74 – 0,82
This paper	Clay (%) Silt (%) Sand (%) Gravel (%) Liquid Limit (%) Plastic Limit (%) Plasticity Index (%) Specific Weight (gr/cm^3)	Data collection	DT SVM k-NN ANN	*Accuracy* DT: 91.50 SVM 89.00 k-NN: 86.00 ANN: 89.00

RFE; Recursive Feature Elimination, *CEB;* Compressed Earth Blocks, *CNN;* Convolutional Neural Network, *GLM;* Generalized Linea Model, *LR;* Logistic Regression, *DF;* Decision Forest, *RF;* Random Forest, *GA;* Genetic Algorithm

The classification of soil types using machine learning methods plays a crucial role in engineering geology. The integration of artificial intelligence, driven by technological advancements, can significantly reduce error rates in such studies. Future research could expand the scope of this study by incorporating additional parameters beyond those used in this paper. Moreover, increasing the number of soil classes with double symbols could help create a more balanced dataset, thereby improving the accuracy rates of soil classifications.

Author contributions Sami Serkan İşoğlu: study conception and design, data collection analysis and, interpretation of results, draft manuscript preparationAhmet Yıldız: interpretation of results, draft manuscript preparationMahmut Mutlutürk: interpretation of results, draft manuscript preparationEnes Cengiz: interpretation of results, draft manuscript preparation.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Competing interests The authors declare no competing interests.

Human ethics and consent to participate Not applicable.

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