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A performance assessment on the implementation of machine learning techniques for prediction of cohesion in fiber reinforced sandy soil

Jun Song [1], Gongxing Yan [2,3], Hamid Assilzadeh[*4,5,6], Rania M. Ghoniem [7], Abdullah Alnutayfat [8], B. Bouallegue [9] and J. Escorcia-Gutierrez[**10]

[1] *Chongqing Chemical Industry Vocational College, Chongqing 401228, China*
[2] *School of Intelligent Construction Luzhou Vocational and Technical College, Luzhou 646000, Sichuan, China*
[3] *Luzhou Key Laboratory of Intelligent Construction and Low-Carbon Technology Luzhou 646000, Sichuan, China*
[4] *Institute of Research and Development, Duy Tan University, Da Nang, Viet Nam*
[5] *School of Engineering & Technology, Duy Tan University, Da Nang, Viet Nam*
[6] *Department of Biomaterials, Saveetha Dental College and Hospital, Saveetha Institute of Medical and Technical Sciences, Chennai 600077, India*
[7] *Department of Information Technology, College of Computer and Information Sciences, Princess Nourah bint Abdulrahman University, P.O. Box 84428, Riyadh 11671, Saudi Arabia*
[8] *Department of Civil Engineering, College of Engineering in Al-Kharj, Prince Sattam Bin Abdulaziz University, Al-Kharj, 11942, Saudi Arabia*
[9] *Department of Computer Engineering, College of Computer Science, King Khalid University, ABHA, 61421, Saudi Arabia*
[10] *Department of Computational Science and Electronics, Universidad de la Costa, CUC, Barranquilla, 080002, Colombia*

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Abstract. A predictive model to determine shear strength and mechanical properties of soil-mix material (soil reinforcement) is required in many geotechnical projects especially when the weight of geomaterial is important for stability or drainage purposes. In this paper, several matching learning (ML) techniques namely Chi-squared Automatic Interaction Detection (CHAID), Classification and Regression Trees (CART), Random Forest (RF), Artificial Neural Network (ANN), Support Vector Machine (SVM), and Generalized Linear Mixed Model (GLMM) were used to predict the effects of reinforcement on cohesion (C) parameter in sandy soil. To establish an appreciate database for prediction purposes, several laboratory tests were planned and conducted on sandy soil mixed with fiber and subsequently, soil properties together with their shear strength parameters were measured. The obtained results from laboratory tests showed that fiber percentage, fiber length, deviator stress and pore water pressure have a significant impact on cohesion values and then, the mentioned parameters were set as inputs. According to the most effective parameters of predictive ML techniques, many models were constructed to predict C of the soil. The modelling results showed that the CHAID model provides the best prediction performance of cohesion in the short term and long term. Coefficient of determination of one and system error of zero for both train and test stages of CHAID have confirmed that this model is a perfect, powerful and applicable ML technique. The design process and model development presented in this study can be considered and used by the other researchers or engineers in resolving their complicated issues.

Keywords: Chi-squared automatic interaction detection; cohesion; fiber material; machine learning; shear strength; soil

1. Introduction

One of the most important parameters in engineering properties of the soil is shear strength that is determined by two main parameters of internal friction angle (φ) and cohesion (C) (Rashid *et al*. 2015, Armaghani *et al*. 2020a). Several direct and indirect methods have introduced to investigate these parameters (Bunawan *et al*. 2018). The experimental techniques, like directional shear test, true triaxial test, triaxial compression test, plane strain compression test, and CPT test (Consoli *et al*. 2005, Das and Basudhar 2008) all known as “direct” category (Wang *et al*. 2023). These approaches are used in the laboratory and in situ and require a noticeable resource of time and cost especially in terms of lab equipment (Donaghe *et al*. 1988, de Blasio 2011). However, this disadvantage encourage using of other techniques that try to benefit from soft computing to estimate important engineering parameters “indirectly” (Gan and Fredlund 1988, Fenton and Griffiths 2003). More recently, regarding the noticeable growth in modelling skills and empirical science, geotechnical studies benefit more and more from the capabilities of these new solutions to determine the engineering properties of soil (Gray and Ohashi 1983, Gray and Al-Refeai 1986, Hua *et al*. 2025). Some of these attempts are finding a correlation between Standard Penetration Test (SPT) and shear strength parameters (Gray and Ohashi 1983), presenting an elastoplastic finite element

*Corresponding author, Ph.D.,
E-mail: fatemehmirzaei@aol.com
**Co-corresponding author, Ph.D., Professor,
E-mail: aaramce@outlook.com

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model to study the effect of C on bearing capacity (Guo 2008). More examples are applying adaptive Neuro-Fuzzy to predict φ (Kayadelen *et al*. 2009), using artificial neural networks (ANNs) to estimate φ in clays, providing two different regression models for the mechanical properties of the soils based on its classification and Atterberg limits (Maher and Gray 1990, Park 2011). Soil reinforcement is one of the most simple and popular methods to improve the shear strength of soils (Hirata *et al*. 1990, Hatanaka and Uchida 1996). In the approach introduced by Vidal and Earth in 1969 (Vidal and Earth 1969) additional materials are known as reinforcement elements and include a variety of natural to artificial materials in form of fiber, shreds, or pieces, mixed to the soil (Penumadu and Zhao 1999). Although this field of studies always has presented significant promising results during the last decades, the scope of the field expands more and more under the influence of the fast growth in sciences and technologies (Armaghani *et al*. 2020a, b). This improvement includes either a variety of reinforcement elements, like recycling artificial waste materials such as polymers and benefit from innovative methods to evaluate the effects of reinforcement. Earlier investigations often used direct laboratory methods (Chahnasir *et al*. 2018, Chen *et al*. 2019, Zheng *et al*. 2025, Zhou *et al*. 2022). For example, using the direct shear test to study sandy soil reinforced with synthetic additives (Ghodsi and Shariati, Xu *et al*. 2022, Meng, *et al*. 2024), the reinforced sand investigation by triaxial compression tests (Gao *et al*. 2020, Chen *et al*. 2019), studying effects of fiber on soil strength by experimental and analytical methods (Ghodsi and Shariati, Heydari and Shariati 2018), stiffness studies on fiber-reinforced granular soil (Hosur Shivaramaiah *et al*. 2022), evaluation of compressive strength and ductility of fiberreinforced cemented sand (Karami *et al*. 2019a, Jahandari *et al*. 2022). However, indirect methods have used to studying reinforced soil as well (Zhao *et al*. 2025a, b). First attempts considered a force equilibrium for the role of the fiber in the mixed material (Kasnavi *et al*. 2018, Karami *et al*. 2019b). Prediction of the failure mood and the shear strength of fiber-reinforced soil (Khojastehkey *et al*. 2016), the relation between φ and clay content (Katebi *et al*. 2019), Atterberg limits (Khorami *et al*. 2017a) or ΔPI which result in predicting shear strength parameters of soil using the empirical formula (Khorami *et al*. 2017b), using Cam Clay model to estimate the deviator stress in reinforced clays (Khojastehkey *et al*. 2015, Katebi *et al*. 2020) are other significant related works. While these attempts approve the high potential of indirect methods to forecast the shear strength parameters of reinforced soils, a growing number of artificial intelligence (AI) and machine learning (ML) approaches has introduced in recent years for solving different problems in science and engineering (Khorami *et al*. 2017c, Khorramian *et al*. 2017). Regarding the remarkable capability of AI and ML techniques in solving complex nonlinear problems with multiple input parameters, recent studies have proved they can be an ideal option to be implemented in geotechnical engineering field. Examples of AI methods are gene expression programming (Li *et al*. 2019, Mehrabi *et al*. 2021), fuzzy system (Milovančević *et al*. 2019), particle swarm optimization (PSO) (Mohammadhassani *et al*. 2013, 2014), adaptive neuro-fuzzy inference system (ANFIS) (Nosrati *et al*. 2018, Naghipour *et al*. 2020) and ANN (Paknahad *et al*. 2018). ML approaches that have applied in geotechnical studies are Chi-squared automatic interaction detection (CHAID) that used to assess medium-scale landslide susceptibility (Razavian *et al*. 2020, Rajaei *et al*. 2021) or to predict the tunnel boring machine penetration rate. Besides, Classification and Regression Trees (CART) as a basic ML model, has introduced in several fields of geotechnical engineering (Chahnasir *et al*. 2018). Trying to obtain a high accuracy level for prediction purposes, supervised ML techniques such as Support Vector Machine (SVM) are desirable option for different geotechnical applications (Safa *et al*. 2019a, Wang *et al*. 2024a, b, c, d). Using SVM to study the settlement in shallow foundations (Safa *et al*. 2019a, 2020) or evaluation of slope stability (Sajedi and Shariati 2019, Saki *et al*. 2024) are good examples of acceptable results that confirm the ML models can be applied in geotechnical studies (Sedghi *et al*. 2018). Specifically, in the area of mixed soil and soil reinforcement, AI/ML models have been effectively applied for solving different problems (Shah *et al*. 2016, Shadpour *et al*. 2019). For example, friction angle as an indicator of shear strength was considered as the target of a hybrid ANN model. The friction angle values of sandy soil mixed with fiber were predicted with an acceptable level of accuracy. In another study, similar techniques were used to forecast the uniaxial strength of clay material mixed with recycled tiles. A radial basis neural network technique was also suggested as a reliable and highly accurate model to predict soil strength reinforced with jute and steel fiber. A series of AI/ML models were employed and the best of them were introduced for soil classification (Shariat *et al*. 2018, Shariati *et al*. 2020a). The soil classifications were done through the use of other soil index tests in laboratory or applying in-situ geophysical investigation (Shariati *et al*. 2019a, 2021a). Of course, other data process or input preparation techniques are available in laboratory of field. It seems that AI/ML techniques with their inside powerful calculations are able to have good solutions for geotechnical applications (Shariati *et al*. 2019b, 2021a). In this article, the results of a series of triaxial tests on fiber reinforced soil were used to introduce six ML/AI models including CHAID, CART, Random Forest (RF), ANN, SVM and Generalized Linear Mixed Model (GLMM) (Shariati *et al*. 2020b). The mentioned techniques which are from different categories with various calculations and backgrounds, were selected to understand their capability in estimating cohesion values of reinforced geomaterial (Shariati *et al*. 2019b, 2020b). These models use the parameters of mixed soil and tests as inputs to predict the geomaterial cohesion as a key parameter in the shear strength of reinforced soil as output. In the following, first, applied AI/ML models and their behind definitions/calculations are introduced (Shariati *et al*. 2019c, 2021b). Then, the laboratory investigations that provide the data for AI/ML models are explained in detail. After that, the process of AI/ML model development will discuss in detail to predict geomaterial cohesion values (Shariati *et al*. 2019d, 2023). Finally, based on the results of model development and model assessment, the best model to predict the cohesion of the reinforced sandy soil will introduce.

2. Methods

2.1 Machine learning techniques

2.1.1 Chi-squared Automatic Interaction Detection (*CHAID*)

A helpful method for identifying the most homogenous groupings in data is CHAID. For classified dependent variables, it is an adaptation of the Automatic Interaction Detection (AID) approach. In 1980, CHAID was introduced as a data mining method. The goal of this approach is to forecast the independent parameter using a tree-based structure of the dependent parameters that are first specified by a number of group rules (Shariati *et al*. 2020c). The correctness of the developed rules is determined by the ratio of the records that display a certain value for the target variable to the values provided for the independent variables (Li *et al*. 2024, 2025). A decision tree (DT) expands a large number of sequential possibilities, which are then divided based on the Chi-Square test. As a result, the CHAID method automatically prunes the DT to prevent overfitting while creating broader, non-binary trees.

2.1.2 Classification and Regression Trees (*CART*)

By selecting the optimal data partition and creating two indices—the Gini impurity and the Twoing criterion—CART (Classification and Regression Trees) seeks to improve prediction accuracy by minimizing the impurity of the leaf nodes (Qiu *et al*. 2025). This method aims to identify the optimal split by building a binary decision tree (DT). In CART, any type of input variable can be practically ordered from smallest to largest values, and a trial split is used to determine the best split point (Wang *et al*. 2024a, b, c). For example, using ‘S’ as a split point, all instances where the value is less than ‘S’ (X < S) are assigned to the left child node, while all instances where the value is greater than ‘S’ (X > S) are assigned to the right child node (Shariati *et al*. 2020d, 2022).

2.1.3 Random Forest (*RF*)

By combining a lot of decision trees, RF’s primary advantage as a machine learning technique is its capacity to provide predictions that are more accurate. Each ensemble member is constructed using a distinct training dataset in this approach, which employs the bagging technique. Therefore, as samples have picked randomly from the decision trees, it results in less diversity in predictions of the method. However, decision trees show a higher variance because of their instability, and therefore any small changes in the training data lead to different generalization behavior (Shariati *et al*. 2019e, 2020e).

2.1.4 Artificial Neural Network (*ANN*)

Discovering the biological neurons and their behavior and connections inspires scientists to define a mathematical model with the structure of an artificial neuron and sigmoid activation functions named ANN (Shariati *et al*. 2019e, 2021c). However, this similarity is limited to morphological, because the science of Biological Neural Networks (BNNs) covers just a small part of the topic. Following the improvements in these kinds of modelling technics, ANNs have introduced that are non-linear statistical data modelling techniques. ANNs especially are powerful in finding patterns in data or determine relations between inputs (dependent parameters) and output (independent parameters). Using assigning positive and negative weights, they can define the connections and their type (i.e., excitatory or inhibitory) between biological neurons. These futures make them a good option for decision-making purposes in different fields like function approximation, classification, and data processing.

2.1.5 Support Vector Machine (*SVM*)

Support Vector Machines (SVM) are powerful classification tools for high-dimensional and linearly non-separable datasets, as demonstrated in prior research (Shariati *et al*. 2019f, 2021c, Xu *et al*. 2024). An SVM classifier aims to find the optimal separating hyperplane to distinguish between two classes. Other studies have shown that the performance of SVMs can also be influenced by the choice of kernel functions, such as linear, radial basis function (RBF), sigmoid, and polynomial kernels (Shariati *et al*. 2024a, b). It is important to note that SVMs are widely favored for both classification and regression tasks because of two major advantages: lower training and testing errors, and reduced model complexity (Shariati *et al*. 2019f, 2020f).

2.1.6 Generalized Linear Mixed Model (*GLMM*)

The Generalized Linear Mixed Model (GLMM) as an extension of the Generalized Linear Model (GLM). In this method, random effects that have added to the linear predictor, insert the correlation via random effects to the primitive ability to model the non-linear distributions (Shariati *et al*. 2019g, 2021d). Table 1 presents the parameters used in the modeling of six ML techniques in this study.

2.2 Performance assessment of the proposed models

The authors of this study used four statistical indicators: Variance Accounted For (VAF%), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2). These indicators, commonly employed in previous related studies (Shariati *et al*. 2018, 2020g), were used to evaluate the accuracy and predictive performance of the developed models. The formulas for calculating these indicators are as follows

$$VAF = \left[1 - \frac{\mathrm{var}(y - y')}{\mathrm{var}(y)}\right] \times 100 \tag{1}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (y - y')^2} \tag{2}$$

Table 1 Parameters used for developing the six models

CHAID	ANN
Tree growing algorithm: CHAID	ANN model: Multilayer Perceptron (MLP)
Maximum tree depth: 5	Stopping rules: use maximum training time (per component model): 15 minutes
Minimum records in parent branch (%): 2	
	Combining rule for continuous targets: mean
Minimum records in child branch (%): 1	
Combining rule for continuous targets: mean	Number of component models for boosting and/or bagging: 10
Number of component models for boosting and/or bagging:	Over fit prevention set (%): 30
10	
Significance level for splitting: 0.05	Missing values in predictors: delete list wise
Significance level for merging: 0.05	
Adjust significance values using Boferroni method Minimum change in expected cell frequencies: 0.001 Maximum iterations for convergence: 100	
CART	**SVM**
Maximum tree depth: 5 Prune tree to avoid overfitting: maximum surrogates: 5 Minimum records in parent branch (%): 2 Minimum records in child branch (%): 1 Combining rule for continuous targets: mean Number of component models for boosting and/or bagging: 10 Minimum change in impurity: 0.0001 Over fit prevention set (%): 30	Stopping criteria: 1.E-3 Regularization parameter (C): 10 Regression precision (epsilon): 0.1 Kernel type: RBF RBF gamma: 0.1
RF	**GLMM**
Maximum percentage of missing values: 70 Exclude fields with a single category majority over (%): 95 Maximum number of field categories: 49 Minimum field variation: 0.05 Number of bins: 10 Number of models to build: 100 Maximum number of nodes: 10000 Maximum tree depth: 10 Minimum child node size: 51	Sorting order: ascending Maximum iterations: 100 Confidence level: 95.0 Degrees of freedom: fixed for all tests Tests of fixed effects and coefficients: assume model assumptions are correct Parameter convergence: 0.000001 Type of convergence criteria: absolute Maximum Fisher scoring steps: 0

$$R^2 = 1 - \frac{\sum_i (y_i - f_i)^2}{\sum_i (y_i - \bar{y})^2} \tag{3}$$

$$MAE = \frac{1}{N}\sum_{j=1}^{N} |y_i - y_j| \tag{4}$$

Here, N is the total number of data points, y represents the observed values, ȳ is the mean of the observed values, and ŷ is the predicted value of y. Following the methodology used in previous comparable studies (Shariati *et al*. 2017), the dataset was randomly divided into two stages: training and testing. In this study, nine samples (30% of the dataset) are used for testing the models, while 21 samples (70% of the dataset) are used for training. The overall performance of each model is evaluated separately for the training and testing datasets (Shariati and Haghighi 2010, Toghroli *et al*. 2020a). Since this study considers six models, the best-performing model for each performance dex receives a score of 6, meaning the maximum possible in rate for each performance index is 6. A model's overall performance rating is calculated by summing its total rank from the training phase and the testing phase. Details of the ranking system can be found in (Shariati *et al*. 2019h). Additionally, the a20-index, proposed for assessing the reliability of the developed ML models, is defined below, following the methodology of other previously published engineering indices (Toghroli *et al*. 2014, 2020b)

$$a20 - \text{index} = \frac{m20}{M} \tag{5}$$

Here, m20 is the number of samples whose experimental value to predicted value ratios fall between 0.80 and 1.20, and M is the total number of samples in the dataset. For an ideal prediction model, the a20-index should be equal to 1. The proposed a20-index can also add physical engineering significance by indicating the number of samples that meet the expected values within a ±20% variance from the experimental values.

Table 2 Soil and fiber properties

Fiber properties		Sand properties	
Property	Value	Property	Value
Density (kN/m^3)	9.1	Maximum dry density ($\mathrm{N/m^3}$)	18.4
Water absorption (%)	13.97	Plasticity (%)	0
Elasticity module ($\mathrm{N/mm^2}$)	104.99	Optimum moisture content (%)	15.4
Tensile strength (N)	309		
Ultimate strain (%)	27.99		

3. Experimental database

3.1 Materials and test specimens

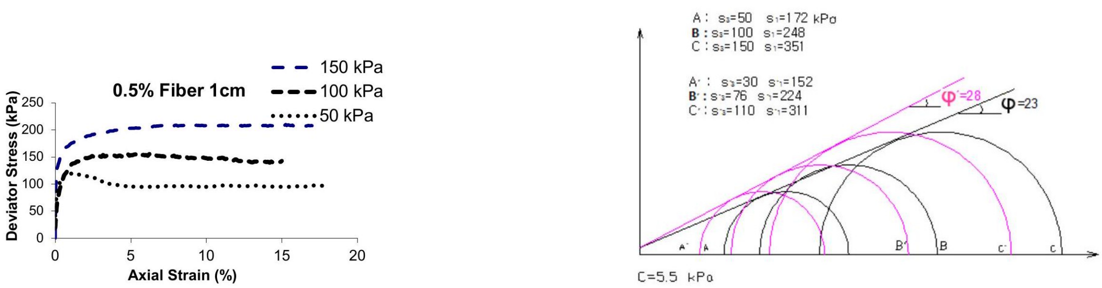
In this research, a new mixed material composed of sandy soil reinforced with fiber is tested and the optimal amount of fiber that yields the most increase in shear strength of the soil is determined. Using 30 triaxial tests, the effect of various weight contents and different lengths of fiber as the main variables has examined. The engineering properties of soil and fiber were determined initially. The tested material is composed of relatively uniformly graded sand with low content of silt classified as SP according to the Unified Soil Classification System (USCS-ASTM D 2487) with polypropylene fiber named DTY (Dipped Tire Yarn) that are considered as waste material of tire factory. The main advantages of this kind of fiber are high tensile strength and fatigue strength. The properties of soil and fiber have presented in Table 2. The triaxial specimens prepared by RDFR (randomly distributed fiber reinforcement) that lead to mobilization of the friction between soil particles and the fiber as tensile components (Toghroli *et al*. 2018a, b). To achieve a homogeneous mixture of soil and fiber, the material was compacted in six layers using the under-compaction method in a cylindrical specimen mold with a height of 150 mm and a diameter of 70 mm. All soil specimens were prepared uniformly, allowing the assumption of isotropy. The density and moisture content of the soil specimens were measured, yielding a density of 15.4 kN/m³ and a constant moisture content of 12%.

3.2 Test procedure

A series of 30 consolidated undrained (CU) triaxial tests have carried out according to American Society for Testing and Materials (ASTM) D 4767-88 standard to evaluate the stress-strain behaviour and shear strength of fiber-reinforced soil. The used apparatus was a three-dimensional fully automated and hydroelectric Canadian geotechnical consulting and testing system (GCTS) triaxial machine, in the Soil Mechanics Laboratory in Bu-Ali Sina University (Fig. 1). These samples were prepared to conduct CU tests with four different fiber weight contents ($0, 0.5\%, 1.0\%$ and 1.5%), three fiber's length (1,2 and 3 cm), and three confining pressure (50,100 and 150 kPa).

The process of saturation and consolidation was performed for all specimens before running the CU tests conducted in laboratory. The B coefficient of Skempton

Fig. 1 GCTS triaxial apparatus used in study



(a) Stress-strain diagram

(b) Mohr-Coulomb failure envelopes

Fig. 2 The diagrams for 0.5% fiber 1 cm

Table 3 Summary of all CU test results (Δσ: deviator stress, u: pore pressure)

Fiber (%)	0%		0.5%						1%						1.5%					
Fiber length	-	-	1 cm		2 cm		3 cm		1 cm		2 cm		3 cm		1 cm		2 cm		3 cm	
Confining stress	$\Delta\sigma$	u	$\Delta\sigma$	u	$\Delta\sigma$	u	$\Delta\sigma$	u	$\Delta\sigma$	u	$\Delta\sigma$	u	$\Delta\sigma$	u	$\Delta\sigma$	u	$\Delta\sigma$	u	$\Delta\sigma$	u
50	60	15	122	20	128	23	147	24	110	15	144	22	151	23	85	16	105	19	142	21
100	114	38	148	24	198	32	220	40	184	22	240	41	245	44	133	33	170	28	240	35
150	170	45	201	40	270	50	300	61	254	33	317	63	335	65	202	41	240	55	320	58
φ (°)	21		23		25		26		25		28		29		22		23		29	
C (kPa)	0		5.5		15.65		22.8		12.5		18.1		17.6		7.4		14.4		14.6	

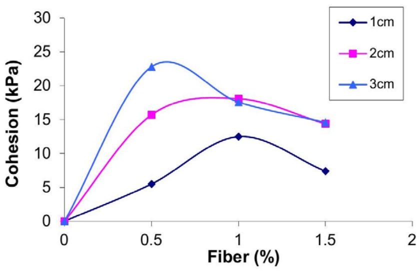


Fig. 3 Changes in cohesion (c) in terms of length and percentage of fiber

pore pressure for all specimens exceeded 0.98%. After the consolidation was completed under confining stress, backpressure was blocked to prevent drainage during the test (Wang *et al*. 2024a, b, c). Then with a controlled strain rate of 0.15% per minute, the compression load was applied. There were two ways of ending the tests; 1) the sample loaded under the stress until the strain reaches to 20%, 2) failure of the specimen.

3.3 Test results

Using the stress-strain diagram as the output of the apparatus, three curves have prepared for the specific fiber content and fiber length tested using three different confining pressures. To assess the internal frictional angle (φ) and cohesion (C) of specimens, using data from the stress-strain diagrams, the Mohr-Coulomb failure envelopes have drawn. The results for 0.5% fiber 1 cm are shown in Fig. 2. Additionally, a summary of all test results are presented in Table 3.

The results admit that adding the fiber can improve the shear strength of the soil. The review of all results summarize as:

1- Fiber reinforcement improves the shear strength of sandy soil.

2- Enhancement in soil shear strength mainly attributes to fiber tensile strength and frictional interaction between fiber and soil particles.

3- Confining pressure plays an indirect mobilization role in shear strength improvement.

4- Fiber can effectively enhance the internal friction angle and cohesion of soil.

5- The fiber reinforcement can add plasticity and shape ability to sandy soils.

3.3.1 Cohesion (C)

In this investigation, adding fiber successfully has increased the shear strength parameters of the soil (Su *et al*. 2021). The cohesionless sandy soil shows cohesion for all reinforced samples and it increases from 0 for unreinforced sample, to 22.8 kPa for sample reinforced with 0.5% fiber 3 cm. Fig. 3 displays the changes in the C for all tests, which confirm the potential of soil reinforcement on improving soil cohesion.

According to Fig. 3, the increase in fiber content up to 1.0% will cause to improve cohesion values, but after this optimal percentage, the amount of C were decreased again. However, the only exception to this trend is for 3 cm fiber that delivered the highest improvement for C in 0.5% that is the highest result for C too. According to the obtained results, it is obvious that fiber length can have a higher level of improvement in the strength rather than fiber content. It attributes to high tensile resistance of fiber that is mobilized under stresses. Moreover, tensile forces raise in the specimens during the test are definitely lower than the maximum tensile strength of fiber (309N) so that tension failure of fibers never would be the case. Other literature reported the dominance of slipping and not rupturing failure mechanism as the result of the high tensile resistance of fiber too (Trung *et al*. 2019a, Toghroli *et al*. 2020c).

3.3.2 Key parameters in tests

This investigation aims to predict the improvement of shear strength in reinforced granular soil by using models based on laboratory studies. To introduce the models, the effective variables should be identified initially. Based on the results obtained in laboratory, in addition to fiber percentage and length that shows a direct effect on improvement of C values, there are other parameters like

Table 3 Descriptive statistics of the experimental database in this research

Parameter/Category	Unit	Range
Percentage of fiber/Input	%	0-2
Length of fiber/Input	cm	0-3
Deviator stress/Input	kPa	60-335
Pore water pressure/Input	kPa	15-65
Cohesion/Output	kPa	0-22.8

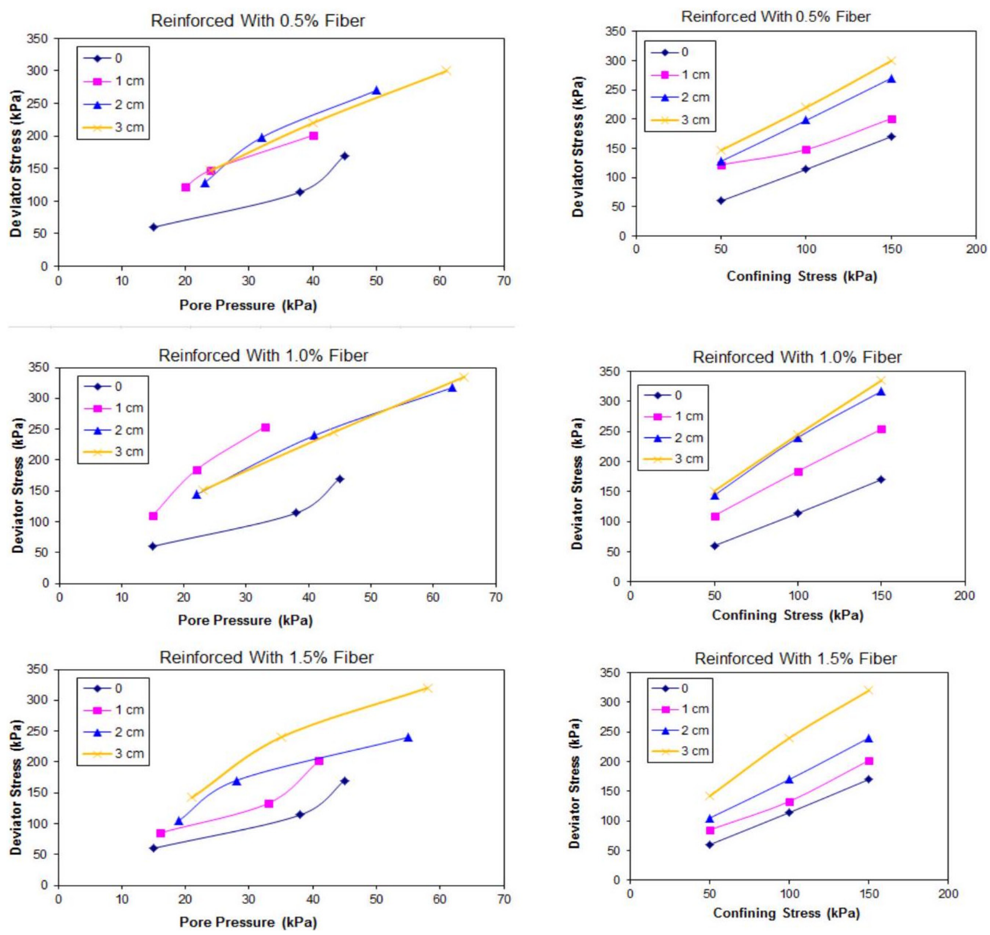


Fig. 4 Effects of fiber presence and confining stress on $\Delta\sigma$ and u

deviator stress ($\Delta\sigma$) and pore water pressure (u) that are important enough to put as input variables for predictive models. According to previous investigations (Trung *et al*. 2019, Wang *et al*. 2022), as long as the variable has a relationship with target of the study or an effect on it, the same variable can choose as the input parameter or predictor to predict target. In the following, more discussions will be delivered about the possible effective factors or input parameters. Fiber content (%) and length (cm): According to Table 3, either fiber percentage and fiber length play pivotal role in increasing the strength of the reinforced samples, however without any exception, more improvement in C and φ related to longer fiber. The authors believe that defining an optimum value for these two parameters would be of advantages. According to Table 3 and Fig. 3, the 1.0% fiber content and fiber with 1.5 cm length, received the best results. Although the positive effect of higher fiber length contributed to more tensile resistance of fiber, after a specific amount of fiber, the interaction between soil particles weaken by excess fiber, which decreases the shear strength and govern the behavior of reinforced soil. Confining Pressure: The confining stresses have an indirect effect in enhancing the results of reinforcement. It determines the performance of fiber by raising the pull out resistance of fiber in higher confining stresses and governs the pore pressure changes (Peng *et al*. 2024, Gao *et al*. 2025). Pore Pressure (u): Pore pressure fluctuation during the test directly affected by confining stress. As all tests performed in consolidated undrained condition, blocked drainage during increase in deviator stress, present itself as an increasing pore water pressure due in the specimen. Deviator Stress ($\boldsymbol{\Delta}\sigma\sigma$: According to Table 3, samples with higher fiber content experience higher deviator stress during the conducted tests. It seems that the frictional nature of interaction between fiber and soil under stress, present itself as a kind of additional confinement effect. This simply leads to the necessity of higher deviator stress to occur failure during the tests with run at higher confining stress. In other word, as presented in Fig. 4, samples with more fiber length and higher fiber percentage can undergo bigger deviator stress and higher pore pressure. Moreover, this effect enhances in higher confining stress.

Soil deformation the fiber reinforcement improves the elastic behaviour of sandy soil under shear stresses. Regarding stress-strain diagrams, lower initial slope of the curves and the increased strain at the failure point are evidence of the fact that reinforced soil act softer rather than more fragile. Therefore, another output of reinforcement can be described as the changing of the soil behaviour to more elastic.

Table 5 Performance indices results for all ML/AI applied models to predict C

		$\mathbf{R}^{2(1)}$		RMSE$^{(2)}$		$\mathbf{VAF}^{(3)}$ (%)		MAE$^{(4)}$		a20index$^{(5)}$		Total rank for each set	Final rank
Model	Dataset	Value	Rank	Value	Rank	Value	Rank	Value	Rank	Value	Rank		
RF	TR	0.94	4	1.76	4	93.84	4	1.41	4	0.24	4	20	38
	TE	0.53	3	3.24	5	36.17	3	2.77	3	0.13	4	18	
CART	TR	0.97	5	1.33	5	96.51	5	0.50	5	0.27	5	25 25	49
	TE	0.65	5	3.28	4	53.17	5	2.07	5	0.16	5	24	
CHAID	TR	1.00	6	0.00	6	100.0	6	0.00	6	0.28	6	30	60
	TE	1.00	6	0.00	6	100.0	6	0.00	6	0.23	6	30	
ANN	TR	0.88	3	2.45	3	87.60	3	1.87	3	0.17	2	14	26
	TE	0.64	4	3.71	2	23.02	2	3.15	2	0.10	2	12	
SVM	TR	0.86	2	4.83	1	56.46	1	3.54	2	0.18	3	9	25
	TE	0.50	2	3.37	3	41.81	4	2.52	4	0.12	3	16	
GLMM	TR	0.65	1	4.37	2	60.70	2	3.62	1	0.13	1	7	12
	TE	0.33	1	4.39	1	-8.80	1	3.79	1	0.06	1	5	

3.4 Selection of model input parameters

Aiming to find an effective model (which is intelligent) for forecasting cohesion of reinforced soil (sandy soil with fiber), six AI/ML models/approaches (including CHAID, CART, RF, ANN, SVM, and GLMM) have been selected and constructed. Based on laboratory tests results and the similar published investigations, four parameters i.e. fiber percentage, fiber length, deviator stress, and pore water pressure were selected as model inputs for prediction of the cohesion of fiber-reinforced sandy soil as target of the research. Table 4 shows the ranges of the input and the output parameters used in this study. In fact, after completing laboratory tests, the results assessed, the key parameters were selected as model inputs. As shown in Table 4, a range of $0-22.8\,\text{kPa}$ was recorded for cohesion of the mixed sandy soil with fiber for different tests conducted in this study. Of course, $\mathrm{C}=0$ is related to the base model which is purely sandy soil without any combination of fiber.

4. Results and discussion

Six AI/ML approaches were selected and proposed in this research to predict C values of the reinforced soil and then, these models were evaluated considering and calculating five performance indices (as discussed before). The most effective factors for each predictive system have considered and applied to the modelling to get the best results. Then, the best model of each predictive system was selected and all five statistical measures were calculated for both train and test stages as shown in Table 5. Based on this table, it is obvious that selecting the best predictive model should be done through a systematic procedure. Therefore, a ranking system was used. This ranking system benefits from a simple procedure of assigning the highest rank values to the best performance (a more accurate one) and the lowest rank values to the worst performance. This

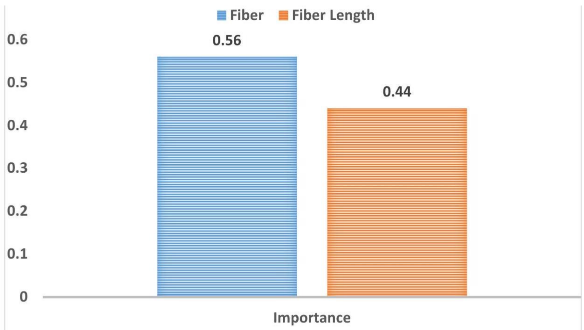


Fig. 5 Importance values of input variables on cohesion of the reinforced sandy soil

process has been conducted for all performance indices as well as train and test stages. Afterward, the ranking of each train and test stage will be summed for each predictive model as the final rank in Table 5 (the last column). The results showed that the CHAID model (with a final rank of 60) obtained the highest rank followed by CART model (with a final rank of 49), RF (final rank of 38), ANN (final rank of 26), SVM (final rank of 25) and GLMM (final rank of 12). As can be seen, selecting the best model without using the ranking system was very difficult. According to Table 5, the proposed CHAID model is a perfect predictive model with R^2 of one, MAE and RMSE of 0, and VAF of 100%. In addition, results of a20-index are very close to zero, which shows that CHAID is a powerful and applicable model to predict soil shear strength parameters (Xie *et al.* 2019, Xu *et al.* 2019). The findings of this study suggest that CHAID is a stable model to predict the soil shear strength parameters since both training and testing R^2 was the same despite the small sample size used in this study. The CART and RF models are wellknown for their capabilities to deal with the instability of single decision trees; however, perfect accuracy of CHAID showed that this model is more efficient than CART and RF to handle the small datasets. The weaker performance of the CART and

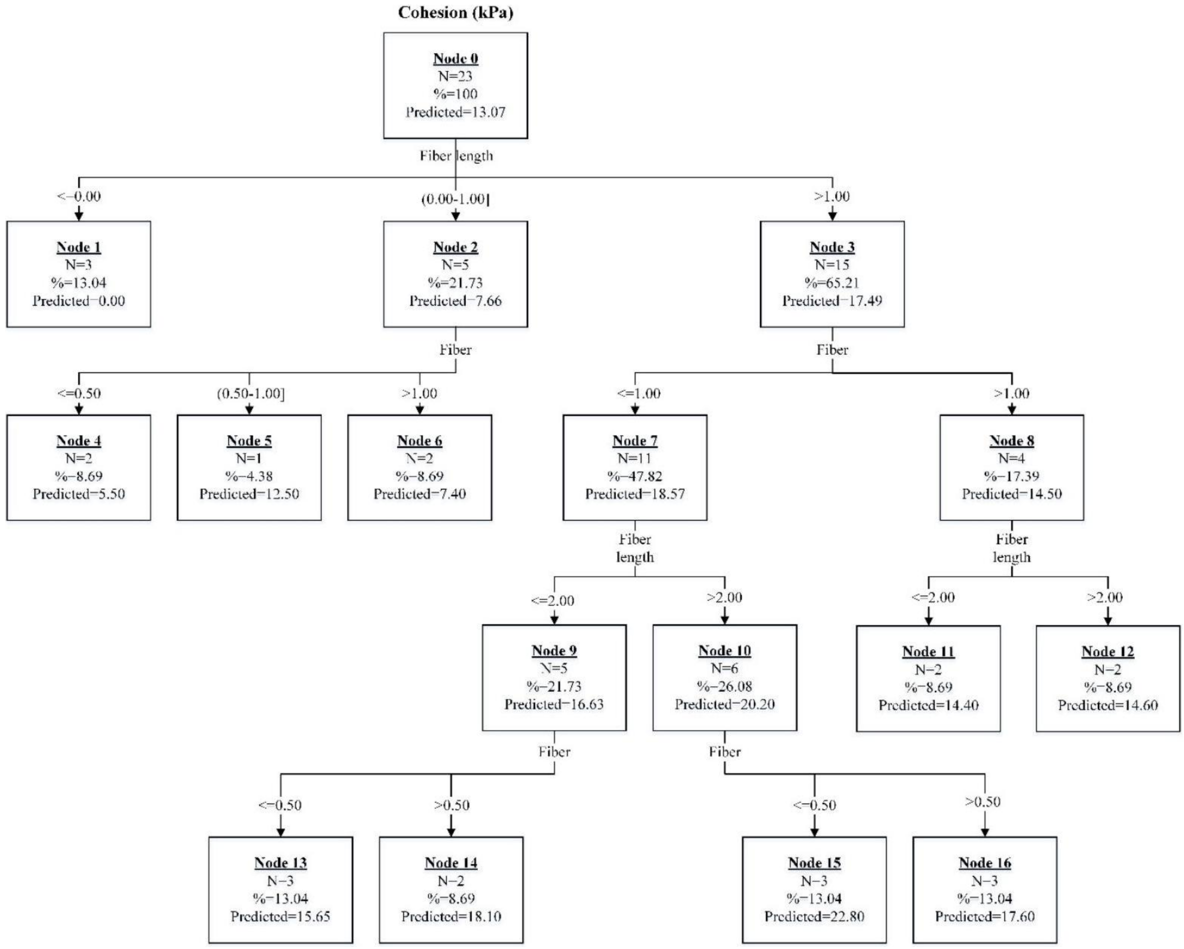


Fig. 6 CHAID tree model of cohesion

RF than other single decision trees might stem from its vulnerability to imbalance data and impacts of fluctuations correlations (Wei *et al*. 2018, Wang *et al*. 2022). Since the CHAID model was selected as the best predictive model in forecasting cohesion of the soil, more details regarding this model are obtained and discussed here. During modelling of CHAID, both deviator stress and the pore water pressure were removed by the system. Consequently, only two parameters of fiber percentage and fiber length remained to predict soil cohesion. This is in line with the results of experimental laboratory works and also previous relevant investigations (Zandi *et al*. 2018, Ziaei-Nia *et al*. 2018). The importance of these two parameters i.e., fiber percentage and fiber length are shown in Fig. 5.

Based on this figure, fiber percentage has the deepest effects on the results with a value of 0.56, while fiber length has an importance value of 0.44 on the soil cohesion. The tree structure flowchart obtained by the developed CHAID model in predicting soil cohesion is displayed in Fig. 6. This tree structure is based on 16 numbers of nodes with different values and percentages of fiber and fiber length. The results of CHAID modelling showed that it is a perfect model in order to be used in the field of soil mechanics. It is important to emphasize that the same CHAID procedure of modelling was applied for the other five models to examine their power and accuracy for cohesion prediction. From these five models, GLMM and ANN are neuron-based models, CART and RF are tree-regression-based and SVM is a regression-based technique. The authors of this study constructed and compared these techniques to understand the performance of different techniques with various calculation background in estimating cohesion values of reinforced soil material. This is a common practice in simulation works specially when there is no previous investigation in that specific field. Laboratory test results showed that the shear strength parameters of sandy soil treated with fiber increase significantly because of high tensile resistance of fiber that is mobilized under stresses. The simulation part of this study indicated that ML/AI models are able to provide a high degree of accuracy for prediction of cohesion. The models and their construction process in this investigation can be used for similar cases and in practice when a cohesion determination is required.

5. Conclusions

In this study, with the aim of soil shear strength prediction, a series of laboratory frameworks have been planned and conducted on the soil samples mixed with the material. The selected material in order to be mixed with sandy soil was fiber. So, the sandy soil was reinforced with different percentages and lengths of fiber material. Then, triaxial compression tests were carried out to measure soil shear strength parameters. Afterward, the cohesion of the soil was selected as model output and six ML models i.e., CHAID, CART, RF, ANN, SVM, and GLMM were used and developed to predict this parameter. These ML models were conducted based on their most effective parameters and the best one in each category was selected. Then, the performance of the best six models of CHAID, CART, RF, ANN, SVM, and GLMM, was evaluated using performance indices and a simple ranking system. The results showed that the highest and lowest final ranking values were obtained as 60 and 12, respectively by the CHAID and GLMM models. According to the results of this study, CHAID model with R^2, system error, VAF, and a-20 index of $(1{,}0{,}100\%$ and $0.28)$ and $(1{,}0{,}100\%$ and $0.23)$ is considered as a perfect, powerful and applicable system for prediction of soil shear strength parameters. The modeling process of this study can be used in similar fields and for prediction purposes with caution. In addition, the developed models of this study can be useful for relevant researchers and engineers to determine shear strength parameters and use in initial design of geotechnical structures. It is important to mention that the range and variation of input parameters should be the same as ranges introduced in this study. Of course, the model will not be applicable for the other situations apart from this study.

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