Prediction of Undrained Shear Strength of Crushed Tire Mixture with Fine-Grained Soil by using Machine Learning Approaches

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Prediction of Undrained Shear Strength of Crushed Tire Mixture with Fine-Grained Soil by using Machine Learning Approaches

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Prediction of Undrained Shear Strength of Crushed Tire Mixture with Fine-Grained Soil by using Machine Learning Approaches.

Abstract: This research examines the ability of soft computing approaches (i.e. Linear Regression (LR), Gaussian Process regression (GP), Adaptive neuro-fuzzy inference system (ANFIS), Support Vector Machine (SVM) and deep neural network (DNN)) to predict the undrained shear strength (SU) of soil mixed waste crushed tires. Data set consisting of 72 different samples were used and obtained from the laboratory experiments. Out of 72 experimental observations randomly separated 50 observations were selected for model development whereas residual 22 were selected for the validation of the developed models. Input data set consist of vertical stress, percentage of the crushed tire, percentage of clay, size of clay, specific gravity of tires, Liquid limit, Plastic limit and Specific gravity of clay samples were considered as inputs whereas undrained shear strength of stabilized soil using waste crushed tires material (SU) was considered as output. Five most popular goodness fit assessment parameters were used for the comparison among developed models. Results suggest that DNN based model works superior to other developed models for the prediction of SU the soil samples mixed with tires waste material with coefficient of correlation values as 0.9975, 0.9736, Root mean square error values as 2.4198, 7.5319, Mean absolute error values as 1.8407, 6.1870, Scatter index values as 0.0311, 0.0959 and Nash Sutcliffe model efficiency values as 0.9943, 0.9387 for training and testing stage respectively. Sensitivity analyses offer that specific gravity of tires, size of clay and vertical stress were the most influencing variables in the prediction SU the soil samples mixed with tires waste material.

46

47 **Keywords:** Undrained shear strength; waste crushed tires; Deep Neural Network; vertical stress;
48 Soft computing approaches.

49 **Introduction**

50 Waste tires are one of the considerable problems in the world. Every year one and half billions of
51 waste tires has been produced in the world. Moreover, recycling of waste car tires at the end of
52 their lifetime is problematic issue ([https://earthbound.report/2017/06/29/what-can-the-world-do-
53 with-1-5-billion-waste-tyres/](https://earthbound.report/2017/06/29/what-can-the-world-do-with-1-5-billion-waste-tyres/)). Low density, high permanence and low cost of the mixture of soil-
54 tire crushes are the principal parameters for using in earth structures (Al Tabbaa et al., 1997; Lee
55 et al. 1999; Bekhiti et al., 2014 and Sofi 2018). Tang et al., (2007) found out fiber reinforcement
56 raises shear strength and failure strain and reduces the stiffness and varied behavior of cemented
57 soil to a ductility state. Mohanty et al., (2021) stabilized the dispersive soil with cement clinker,
58 ground granulated blast furnace slag (GGBS) and flyash. Results of unconfined compressive
59 strength (UCS) are found to be increased significantly by mixing additives in different
60 proportions. From the results of the UCS tests, the optimum mix proportion was obtained with
61 the mixing of 20% of flyash, 15% of GGBS and 30% of cement clinker in dispersive soil. Jafari
62 and Esna-ashari (2012) reinforced cohesive soil with tire in different freeze-thaw cycles and
63 revealed that fiber is raised the shear strength of the soil when the freeze-thaw cycles enhanced.
64 Kalkan (2013) studied the mixture of tire rubber with cohesive soil and obtained that unconfined
65 compression strength is increased in comparison with pure clay. Promputthangkoona and
66 Karnchanachetanee (2013) stabilized low strength SC soil with a 15% mixture of tire chips and
67 cement and found out that, it decreases road construction cost.

68 Yadav and Tiwari (2017) revealed that fiber mixtures of clay with comment and rubber can be
69 useful for retaining wall, traffic roads, and canals. Al-Neami (2018) mixed 2, 4, 6 and 8% tire
70 chips with sand and revealed considerable decrement in maximum dry density and specific
71 gravity, increment in friction angle, cohesion and load-bearing capacity with increasing crushed
72 tiresin mixed sands. Signes et al., (2016) investigated swelling potential reduction using rubber
73 content in the soil (white argillaceous marlstone).The variation of rubber content was 2.5, 5, 10,
74 15, 20 and 25% in terms of weight. The mixing of rubber content in the soil up to a 15% makes it
75 lighter and less prone to swelling, while compressibility remains same as natural soil and the
76 drained shear strength marginally rises. Rahgozar et al., (2018) researched on the mixture of
77 clayey sand soil with 6% ash and 8% cement during twenty-eight curing time and revealed that
78 the unconfined compression strength is considerably enhanced in comparison with clayey sand
79 specimens. Akbarimehr et al., (2019) studied on mixed clay with waste tire and found that
80 increasing waste materials and granules increases and decreases optimum water content and
81 maximum dry density, respectively.In this research, undrained behavior of mixture of cohesive
82 soil with crushed tire has been studied by tri-axial test based on crushed tire content and
83 plasticity of clay.

84 From last few decades, soft computing techniques such as artificial neural network (ANN),
85 Gaussian process regression, Support vector machines (SVM)) and M5 model tree were
86 successfully used in solution of various engineering related problems (Parsaie and Haghiabi
87 2016; Mohanty et al., 2019; Kumar and Sihag 2019; Al-Gabalawy et al., 2021 a and b; Salmasi
88 et al., 2021; Sihag et al., 2020; Pandhiani et al., 2021; Bhorla et al., 2021, Thakur et al., 2021;
89 Sangeeta et al., 2021). Sihag et al., (2019) used ANFIS, SVM and random forest (RF) for the
90 prediction of cumulative infiltration (CI) and infiltration rate (IR) in arid areas in Iran. Norouzi

et al., (2021) applied ANN, ANFIS, generalized neural network (GRNN), SVM, GP, LR, and multiple linear regression MLR to predict the relative energy dissipation for vertical drops equipped with a horizontal screen and found that the performance of ANFIS model was outperforming among other applied models. The performance of SVM based model was better than ANFIS and RF based model for the prediction of CI and IR. Aradhana et al., (2021) applied Fuzzy Logic, MLR, ANFIS, and ANN for estimation of aeration efficiency at labyrinth weir and found that ANN was the best performing model for the estimation of aeration efficiency. Bong et al., (2020) proposed deep learning and MLR based models for the prediction of Ultimate Bearing Capacity of Aggregate Pier Reinforced Clay and results indicated that both models were suitable for the prediction of ultimate bearing capacity. Keeping in the view the potential of Gaussian process, SVM, ANFIS and DNN approaches; this current investigation explores the potential of these techniques in prediction of SU the soil samples mixed with tires waste material and compares their performance with an empirical relationship developed by Linear regression. As per best authors knowledge no one used these techniques in the prediction SU the soil samples mixed with tires waste material. In this study, four different kernel functions (Normalized polynomial, polynomial, Pearson VII and radial basis) based models performance were also evaluated and compared for the prediction SU the soil samples mixed with tires waste material.

Soft computing Techniques Theory

Gaussian process non-linear regression (GP)

Classification and regression problems are two major parts of supervised learning methods. Among different kinds of approaches, Gaussian process regression is one of the most attractive supervised learning nonparametric approaches to predictions (Seeger, 2004; Rasmussen and Williams, 2006; Shi and Choi, 2011; Kang *et al.*, 2015).

114 Considering a data set $\omega = \{(\mathbf{x}_i, y_i) | i = 1, \dots, n\}$ where $\mathbf{x} \in R^d$ is d-dimensional input vector
 115 space and $y \in R$ is output in 1-dimensional vector space. In the regression approach, the
 116 conditional distribution of outputs due to specific inputs is more interesting for understanding the
 117 relationship between inputs and outputs(actual values). In the Gaussian process a joint Gaussian
 118 distribution covers a set of random variable sample (R.V.S) with any finite number. The
 119 Gaussian process $f(\mathbf{x})$ can specify with mean and covariance function:

120 Mean function $m(\mathbf{x})$:

$$121 \quad m(\mathbf{x}) = E[f(\mathbf{x})] \quad (1)$$

122 Covariance function or kernel function $K(\mathbf{x}, \mathbf{x}')$:

$$123 \quad K(\mathbf{x}, \mathbf{x}') = [(f(\mathbf{x}) - m(\mathbf{x}))(f(\mathbf{x}') - m(\mathbf{x}'))] \quad (2)$$

124 for $\mathbf{x} \in R^d$, with $K_{ij}(\mathbf{x}_i, \mathbf{x}_j)$, $i, j = 1, \dots, n$ for all pair of $\mathbf{x} \in R^d$ could make $K(\mathbf{X}, \mathbf{X})$ as the
 125 covariance matrix.

126 Gaussian process $f(\mathbf{x})$:

$$127 \quad f(\mathbf{x}) = GP(m(\mathbf{x}), K(\mathbf{x}, \mathbf{x}')) \quad (3)$$

128 In the GP nonlinear regression, we interest to understand the relationship between inputs and
 129 outputs. For a set of $\mathbf{x} = (\mathbf{x}_1, \dots, \mathbf{x}_d) \in R^d$, $y(\mathbf{x})$ is a regression model composed of $f(\cdot): R^d \rightarrow$
 130 R as a nonlinear function and ε is Independent and identically distributed (i.i.d) noise $\varepsilon \sim N(0, \sigma^2)$.

$$131 \quad y(\mathbf{x}) = f(\mathbf{x}) + \varepsilon \quad (4)$$

132 In the polynomial model $f(\mathbf{x})$ is: $f(\mathbf{x}) = \sum_{d=1}^d \alpha_d(\mathbf{x})x^d$,

133 the least square theory can use to estimate the coefficient α . In the Gaussian process, we
 134 assume $p(f|\mathbf{x}) \sim N(0, K)$.

135 *Prediction process with noisy dataset* $\mathbf{x}$:

136 if f training output for n training inputs($\mathbf{X}$) and $\mathbf{f}_*$ be test output for n_* test points($\mathbf{X}_*$)the joint
137 distribution as follows:

$$138 \quad \begin{bmatrix} \mathbf{y} \\ \mathbf{f}_* \end{bmatrix} \sim N \left(0, \begin{bmatrix} K(\mathbf{X}, \mathbf{X}) + \sigma_n^2 \mathbf{I} & K(\mathbf{X}, \mathbf{X}_*) \\ K(\mathbf{X}_*, \mathbf{X}) & K(\mathbf{X}_*, \mathbf{X}_*) \end{bmatrix} \right)$$

139 The predictive equation in this process:

$$140 \quad \mathbf{f}_* | \mathbf{X}, \mathbf{y}, \mathbf{X}_* \sim N(\bar{\mathbf{f}}_*, \text{cov}(\mathbf{f}_*))$$

$$141 \quad \bar{\mathbf{f}}_* = K(\mathbf{X}_*, \mathbf{X})[K(\mathbf{X}, \mathbf{X}) + \sigma_n^2 \mathbf{I}]^{-1} \mathbf{y} \quad (5)$$

$$142 \quad \text{cov}(\mathbf{f}_*) = K(\mathbf{X}_*, \mathbf{X}_*) - K(\mathbf{X}_*, \mathbf{X})[K(\mathbf{X}, \mathbf{X}) + \sigma_n^2 \mathbf{I}]^{-1} K \quad (6)$$

143 The mean and variance of $\mathbf{f}_*$ help the process to estimate output.

144 *Training part in this process:*

145 After defining a covariance function, the hyper parameters using max log-likelihood can be
146 learned for maximize process can be provided from some optimization algorithm.

147

148 *Support Vector Machine*

149 Support vector machine as a soft computing approach has represented its exponent in many
150 applications such as regression, classification and forecasting. That (Cortes and Vapnik, 1995)
151 shown a kernel function which is useful in nonlinear regression.

152 for a data set $\omega = \{(\mathbf{x}_i, y_i) | i = 1, \dots, n\}$ where $\mathbf{x} \in R^d$ is d-dimensional input vector space and
153 $\mathbf{y} \in R$ is output in 1-dimensional vector space, SVM regression could estimate the relationship
154 between $\mathbf{x}$ and $\mathbf{y}$. In the SVM approach the risk function is minimized with minimizing both
155 empirical risk and $\|\mathbf{w}\|^2$.

$$R = \frac{1}{2} \|w\|^2 + C_C \sum_{x_i} l_\varepsilon (y_i - f(\vec{x}_i)) \quad (7)$$

where $\|w\|$ is a vector that shows regression of data, l_ε is loss function that presents the aberration between y_i (real output) and $f(\vec{x}_i)$ and C_C as a positive constant value need to fix priory. $l_\varepsilon (y_i - f(\vec{x}_i))$ will be 0 for $|y_i - f(\vec{x}_i)| < \varepsilon$ otherwise will equal to $|y_i - f(\vec{x}_i)|$. Minimizing the risk function could be using the function:

$$f(x, \alpha, \alpha^*) = \sum_{i=1}^l (\alpha_i^* - \alpha_i) (\varphi(x_i), \varphi(x)) + b \quad (8)$$

where $\alpha_i^* \alpha_i = 0$ and $\alpha_i^*, \alpha_i \geq 0$, $(\varphi(x_i), \varphi(x))$ as a inner product is kernel function and b will be bias term (Vapnik, Golowich and Smola, 1997) and (Wang, 2005).

164

165 *Adaptive neuro-fuzzy inference system (ANFIS)*

166 In non-linear modeling, ANFIS as a particular method in neuro-fuzzy system has presented
167 noteworthy results (Jang, Sun and Mizutani, 1997)

168 Sugeno model (Sugeno,1985) is famous method in the fuzzy modeling with significant
169 efficiency. There are two if-then issues in this approach:

170 1. if x is A_1 and y is B_1 , then $z_1 = p_1x + q_1y + r_1$

171 2. if x is A_2 and y is B_2 , then $z_2 = p_2x + q_2y + r_2$

172 A_i and B_i are fuzzy sets and in the training part p_i, q_i and r_i will be estimated.

173 In general, ANFIZ is described using 5 layers:

174 **Layer 1**, $O_i^1 = \mu_{A_i}(x)$, $i = 1, 2$ and $O_i^1 = \mu_{B_i}(y)$ $i = 3, 4$ where μ_{A_i} and μ_{B_i} are membership
175 function of A_i and B_i .

176 **Layer 2**, in this layer the product of multiple incoming signals will be calculated.

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y) \quad i = 1,2 \quad (9)$$

Layer 3, the normalized firing strengths will be the output of this layer.

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \quad (10)$$

Layer 4, in each Node in this layer the contribution of the i^{th} rule to the output of model will be calculated,

$$O_i^4 = \bar{w}_i z_i \quad i = 1,2 \quad (11)$$

Layer 5, the final output will be extracted from this single node,

$$O_i^5 = \sum_{i=1}^2 \bar{w}_i z_i \quad (12)$$

more information about ANFIS readers should be follow (Jang, 1993).

Deep neural network (DNN):

DNN is a hybrid neural network. The processing node is the most basic component of a neural network (NN). Each processing node acts in two ways, similar to a biological neuron. It begins by adding the values of its inputs. This computation is sent through an activation function to produce target values. As an activation function, any differentiable function can be utilized, f . All of the processing nodes in NN are organized into layers, each layer is fully interconnected to the following layer. The nodes of the same stratum do not communicate with each other. In a NN, normally, there is an input layer that serves as a distribution framework of the data being inputted to the network and not used for any kind of processing. This layer is followed by one or more processing layers known as hidden layers. The final processing layer is known as Target layer. A neural network with two or more hidden layers containing large number of nodes and using advanced mathematical modeling is normally known as deep neural network.

All the interconnections among every node have related weight. When a value is transferred from the input layer, down these interconnections, these values are multiplied by the related weight and summed to receive the net input (A_j) to the unit

$$A_j = \sum_i w_{ji} o_i \quad (13)$$

Where w_{ji} is the weight of the interconnection to unit j from unit i (called input) and o_i is the target of the unit i . The net input received by the above equation is then transformed by the activation function to generate a target (o_j) for the unit j .

Most of the studies reporting the implementation of neural network in various engineering fields used learning rates values which were randomly set by the user (a value between 0 and 1) based on the past experiences. To improve the working of traditional gradient descent algorithms, adaptive gradient descent (using adaptive learning rate) algorithms, which could adaptively tune the learning throughout the training process was proposed and used with DNN (Goodfellow et al., 2016). In current investigation, adaptive moment estimation (Kingma and Ba, 2015) based optimization algorithm was used to update network weights during training in place of the classical stochastic gradient descent method.

In deep neural network if training data is limited or small then it may normally over fit (error normally increases), thus generates lower accuracy with test data. To avoid the overfitting issue various regularization methods are selected to improve the accuracy of DNN based models (Goodfellow et al., 2016). To avoid the problem of overfitting, Srivastava et al. (2014) introduced the concept of dropout layer in the design of DNN to improve their accuracy. Dropout is a regularisation technique selected to get better performance of DNN model and by removing

a node arbitrarily, either in hidden or a visible layer, as well as all of its incoming and outgoing connections. This is achieved by randomly setting weights of these nodes to zero (Srivastava et al., 2014). Each node is assigned a probability p , which represents probability of keeping the node during training and ranges between 0 and 1. Except the choice of activation function, dropout layer requires probability of retention in the hidden layers (i.e. p) to be defined by the user which can be optimised through trial and error process.

Similar to simple NN, deep neural network required setting of several user defined parameters. These parameters includes, number of hidden layers, nodes in each hidden layer, activation function for output, hidden and dropout layers, weight initialization method, optimization algorithm, updaters (i.e. learning rate optimization algorithm), batch size (i.e. number of training samples used in one iteration) and number of epochs (i.e. one epoch is defined as when an entire training dataset has passed once through the neural network both in forward and backward direction). To implement DNN, WEKA 3.9.5 was used in this investigation. The Architecture of DNN model for the prediction of undrained shear strength of stabilized soil using waste tires material (SU) is shown in Figure 1

Fig .1 Architecture of DNN for the prediction of undrained shear strength of stabilized soil using waste tires material (SU)

Experimental program

Material and samples

Two different types of clay soils with various plasticity specifications were studied as a cohesive material. The clay soils are introduced with C1 and C2 symbols in this research. Characteristics of selected fine-grained soils are listed in Table 1. Grading curves of used fine-grained are depicted in Figure 2. Three various crushed tires were used in the sizes of 1.38, 2.96, and 4.53 mm and mixed with two different clay soils. These three crushed tires are shown in Figure 3. The sieved tires were named as T1, T2 and T3. Specific gravity of T1, T2 and T3 crushed tires is 0.820, 0.932 and 0.101, respectively.

Fig. 2 Grain size distributions of tested clays.

Figure. 3. Crushed tire in different sizes.

Table 1. Characteristics of material used(clays).

Specification	Liquid limit (%)	Plasticity index (%)	Specific gravity	Soil classification
---------------	------------------	----------------------	------------------	---------------------

C1	31	11	2.72	CL
C2	62	30	2.661	CH

254

255 *Conducted Tests*

256 A number of specimens made of clay and clay mixed with crushed tire were prepared. The
 257 specimens were prepared by dry mixing of clay with tire percentage of 9%, 18%, and 27% by
 258 weight.

259 Direct shear tests (ASTM D6528-17) have been done on the specimens at a constant rate of 0.05
 260 mm/min and in vertical stress of 100, 200 and 300 kPa. For T1C1 and T1C2 specimens the shear
 261 strength of 27% crushed tire mixtures is approximately equal to pure clay (Figure 4a). For T2C1
 262 and T2C2 specimens by increasing 9% crushed tire, shear strength is decreased, thereafter, it
 263 remains constant up to 27% crushed tire mixture (Figure 4b). For T3C1 and T3C2 specimens in
 264 different percentage of crushed tire mixtures, different trends have been observed (Figure 4c). It
 265 can be mentioned that, tiny crushed tires don't change considerably the shear strength of pure
 266 clay.

Figure 4. Shear strength versus crushed tire content

270

271 **Date set**

272 Total 72 experimental observations undrained shear strength of stabilized soil using waste
 273 material are used for model development and validation. Total data set was divided in two
 274 different parts. The process of dividing the data set is randomization. Larger Part (50
 275 observations) is selected for the model development and considered as training data set and
 276 remaining part (testing data set) is used for model validation. Eight independent variables namely
 277 as number of vertical stress (VS), Percentage of crushed tire (T), percentage of Clay (C), Size of
 278 clay (S), Specific gravity of tires (G_{st}), Liquid limit (LL), Plastic limit (PI) and Specific gravity
 279 of clay samples (G_{sc}) were considered as inputs whereas undrained shear strength of stabilized
 280 soil using waste tires material (SU) is considered as target for model development and validation.
 281 Characteristics of the data used for model development and validation are listed in Table 2.

282 **Table 2.** Characteristics of the data set used in this study.

Range	VS	T	C	S	G _{st}	LL	PI	G _{sc}	SU	Data set
Mean	200.0000	13.5000	86.5000	2.9656	0.8907	43.5000	21.0000	2.7000	77.9470	Total
	196.0000	15.3000	84.7000	2.9436	0.8884	42.9600	20.6000	2.7008	77.6903	Training
	209.0909	9.4091	90.5909	3.0155	0.8957	44.7273	21.9091	2.6982	78.5303	Testing
Standard Deviation	82.2226	10.1329	10.1329	1.5345	0.0687	13.5947	10.0702	0.0201	31.8660	Total
	80.7111	10.4847	10.4847	1.5679	0.0707	13.6261	10.0934	0.0202	32.4856	Training
	86.7898	8.0868	8.0868	1.4905	0.0653	13.7605	10.1929	0.0204	31.1486	Testing
Minimum	100.0000	0.0000	73.0000	1.3800	0.8020	30.0000	11.0000	2.6800	24.9240	Total
	100.0000	0.0000	73.0000	1.3800	0.8020	30.0000	11.0000	2.6800	24.9240	Training
	100.0000	0.0000	73.0000	1.3800	0.8020	30.0000	11.0000	2.6800	30.0669	Testing
Maximum	300.0000	27.0000	100.0000	5.7300	0.9680	57.0000	31.0000	2.7200	148.3908	Total
	300.0000	27.0000	100.0000	5.7300	0.9680	57.0000	31.0000	2.7200	148.3908	Training
	300.0000	27.0000	100.0000	5.7300	0.9680	57.0000	31.0000	2.7200	126.8939	Testing
Confidence Level(95.0%)	19.3214	2.3811	2.3811	0.3606	0.0161	3.1946	2.3664	0.0047	7.4881	Total
	22.9378	2.9797	2.9797	0.4456	0.0201	3.8725	2.8685	0.0057	9.2323	Training
	38.4804	3.5855	3.5855	0.6609	0.0290	6.1011	4.5193	0.0090	13.8105	Testing

283

284

Soft Computing and goodness of fit assessment parameters

Regression and soft computing techniques based models (i.e. LR, GP, SVM, ANFIS and DNN) were evaluated against actual values for their capability to predict the SU of stabilized soil using tires waste material. For the model goodness of fit assessment, five statistical parameters, namely, Coefficient of Correlation (CC), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Scatter Index (SI) and Nash-Sutcliffe model efficiency (NE) were selected in this study. The above mentioned goodness of fit assessment parameters can be calculated by the equations as follow:

$$CC = \frac{a \sum AP - (\sum A)(\sum P)}{\sqrt{a(\sum A)^2 - (\sum P)^2} \sqrt{a(\sum A - \sum P)^2}} \quad (14)$$

$$RMSE = \sqrt{\frac{1}{a} (\sum_{i=1}^a (A - P)^2)} \quad (15)$$

$$MAE = \frac{1}{a} |A - P| \quad (16)$$

$$SI = \frac{RMSE}{\bar{A}} \quad (17)$$

$$NE = 1 - \frac{\sum_{i=1}^n (A - P)^2}{\sum_{i=1}^n (A - \bar{A})^2} \quad (18)$$

Where A = Actual, P = Predicted, $\bar{A}$ = mean of actual, a = number of observations.

Result and Discussion:

Results of Linear regression

The LR based model is an empirical equation. The LR equations generated by least square technique to drive regression coefficients using the training data set. XLSTAT software is implemented for the formation of LR based model.

$$SU = 57.1508 + 0.3441 VS - 0.0364 T - 0.9356 S - 36.6385 Gst - 0.2569 LL \quad (19)$$

Figures 5 provides agreement plot among actual and predicted SU of stabilized soil using tires waste material by LR based model for training and testing stages respectively. Five statistical performance assessment parameters were used to evaluate the performance of developed models. The result of LR based model for the training and testing stages are listed in Table 3. It indicates the performance of LR model, higher value of coefficient of correlation, NS and lower value of RMSE, MAE and SI confirms that LR based model is suitable for the predicting the SU of stabilized soil using tires waste material. Further, single factor ANOVA results that F -values (0.109793) was less than f - critical (4.072654) and P - values (0.742027) was greater than 0.05 suggest that difference in predicted values by LR and actual values is insignificant.

Figure 5. Agreement plot among actual and predictedSU of LR model (a) training stage (b) testing stage.

Results of GP based models

Developing the Gaussian process regression-based models (Gaussian noise, d^* , d , γ , σ and ω) is a trial and error process. Four different kernel functions [Normalized poly (NPoly), Polynomial (Poly), Pearson VII(PUK) and Radial basis (RBF)]were used to develop models. Gaussian noise

(0.1) was kept constant for all kernels for the fair comparison of models. The optimum user defined parameters are $d^*(5)$, $d(2)$, $\gamma(1)$, $\omega(8)$ and $\sigma(1)$. Results of the GP based models development and validation are listed in Table 3, it was found that the Poly kernel has a better performance compared with NPoly, RBF and PUK kernel functions. The performance of GP based models in training and testing stage is shown in Figure 6. The value of CC is 0.9732, RMSE value as 8.4458, MAE as 7.1868, SI as 0.1075 and NE 0.9230 was obtained at time of testing of Poly kernel function based GP model. Overall, assessing Figure 6 clearly indicates that the Poly kernel function based GP model is suitable for prediction of the values of SU of the soil samples mixed with tires waste material.

Figure 6.Agreement plot among actual and predicted SU of GP model (a) training stage (b) testing stage.

Results of SVM

Development of the SVM based models is also similar to GP process. Four same kernel functions (NPoly, Poly, PUK and RBF) were used to develop models. Value of C equal to 2 was kept constant for all kernels for the fair comparison of models. The vale optimum user defined parameters are used similar to GP based models for fair comparison among SVM and GP based models. Performance evaluation parameters of the SVM based models development and validation are listed in Table 3, it was found that the Poly kernel has a better performance compared with NPoly, RBF and PUK kernel functions. The performance of SVM based models in training and testing stages are presented in Figure 7.

Figure 7.Agreement plot among actual and predicted SU of SVM model (a) training stage (b) testing stage.

Results of ANFIS:

Developing the Sugeno fuzzy rule-based ANFIS models is trial and error process. Two different shapes (Triangular and Trapezoidal) of the membership functions (MFs) were chosen for developing the models. Results of the ANFIS model to predict the SU of soil mixed with tires waste material is shown in Figure 8. From Table 3, it can be inferred that Trapezoidal-based ANFIS (ANFIS_trapmf) model works better than that triangular MFs based ANFIS model. The value of CC is 0.9145, RMSE value as 15.8496, MAE values is 11.7975, SI value as 0.2018 and NE 0.7288 were obtained during testing stage using trapezoidal MFs based ANFIS model. Overall, revealed by Figure 8, the trapezoidal MFs based ANFIS model is suitable for predicting the values of SU of soil samples mixed with tires waste material.

Figure 8.Agreement plot among actual and predicted SU of ANFIS model (a) training stage (b) testing stage.

Results of DNN:

Development of the DNN based model was also trial and error process. The DNN model was optimized in user defined parameters algorithm used with three hidden layers (100, 80, 60 nodes), epochs =600, batch size =100, instance iterator =10, Activation function ReLU, attribute = normalized the above values were obtained after the optimization of the model based on performance indicators after many trials. Performance evaluation parameters of the DNN based model development and validation are listed in Table 3, it was found that the DNN has a better performance compared with above discussed models with CC values as 0.9736, RMSE values as 7.5319, MAE value as 6.1870, SI value as 0.0959 and NE value as 0.9387 for testing stage. The agreement plots among Actual and predicted values using DNN based model are presented in Figure 9 for training and testing stages.

Figure 9.Agreement plot of actual and predicted of DNN based model using training and testing data set respectively.

397

398 **Table 3.** Goodness of fit assessment parameters calculated for soft computing based models

399 using training and testing data sets

Models	CC	RMSE	MAE	SI	NE
	Training data set				
LR	0.8841	15.0280	12.9284	0.1934	0.7816
GP_NPoly	0.9922	4.0836	3.3885	0.0526	0.9839
GP_Poly	0.9856	5.4386	4.2478	0.0700	0.9714
GP_PUK	1.0000	0.4059	0.3323	0.0052	0.9998
GP_RBF	0.9979	2.1653	1.7806	0.0279	0.9955
SVM_NPoly	0.9764	6.9940	4.0407	0.0900	0.9527
SVM_Poly	0.9799	6.4461	4.1674	0.0830	0.9598
SVM_PUK	1.0000	0.1596	0.1491	0.0021	1.0000
SVM_RBF	0.9952	3.3233	1.5339	0.0428	0.9893
ANFIS_trimf	1.0000	0.0160	0.0083	0.0002	1.0000
ANFIS_trapmf	1.0000	0.1183	0.0491	0.0015	1.0000
DNN	0.9975	2.4198	1.8407	0.0311	0.9943
	Testing data set				
LR	0.8685	15.8129	13.2860	0.2014	0.7300
GP_NPoly	0.9512	10.3178	7.9340	0.1314	0.8851
GP_Poly	0.9732	8.4458	7.1868	0.1075	0.9230
GP_PUK	0.9316	11.9845	9.3703	0.1526	0.8449
GP_RBF	0.9561	9.7258	7.3121	0.1238	0.8979
SVM_NPoly	0.9465	10.4807	8.7570	0.1335	0.8814
SVM_Poly	0.9718	11.2114	8.9219	0.1428	0.8643
SVM_PUK	0.9328	11.8246	9.2327	0.1506	0.8490
SVM_RBF	0.9524	10.1752	7.8761	0.1296	0.8882
ANFIS_trimf	0.7331	31.0174	19.7108	0.3950	-0.0388
ANFIS_trapmf	0.9145	15.8496	11.7975	0.2018	0.7288
DNN	0.9736	7.5319	6.1870	0.0959	0.9387

400

401 *Comparison of soft computing based models*

402 Five standard statistical performance evaluation parameters (CC, RMSE, MAE, SI and

403 NE) are selected to evaluate the goodness of various soft computing based developed models.

404 The values of these performance assessing parameters are listed in Table (3) and shown in Figure

11. Figure (10) shows the agreement, performance and relative error plot of various soft computing based models for testing stage. Figure (10) and Figure 11 suggest that DNN based model works better than other developed models. Polynomial kernel function based models works better than other kernel functions based SVM and GP models. Table 3 and Figure 9 also conclude that trapezoidal MFs based ANFIS models works better than triangular MFs based ANFIS model for the prediction of SU of soil mixed with tires waste material. It can be inferred from this figure that predicted values provided by DNN based model were in very close to line of perfect agreement and predicted SU of soil mixed with tires waste material found to follow the same patterns of actual SU of soil mixed with tires waste material with minimum relative error. Features of the actual and predicted values using soft computing based models for both training and testing stages are summarized in Table (4). Single factor ANOVA results in Table 5 suggest that there is not significant difference among actual and predicted values using various soft computing based models with F values are less than F-critical and P values are greater than 0.05.

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Figure 10. Performance of various regression and soft computing based models (a) agreement plot for training stage (b) agreement plot for testing stage (c) performance plot and (d) relative error plot

Figure 11. Radar Plot of performance evaluation parameters (a) MAE and RMSE (b) CC, SI and NE for testing stage

Table 4. Features of the actual and predicted values using soft computing based models for both training and testing stages.

Actual and models	Mean	Standard Deviation	Minimum	Maximum	Confidence Level(95.0%)
	Training data set				
<i>Actual</i>	77.6904	32.4856	24.9240	148.3910	9.2323
<i>LR</i>	77.6903	28.7205	35.1054	121.6619	8.1623
<i>GP_NPoly</i>	77.6444	31.4692	24.6730	143.6700	8.9435
<i>GP_Poly</i>	77.6938	31.8145	26.6160	138.3280	9.0416
<i>GP_PUK</i>	77.6894	32.2091	25.1750	147.5360	9.1537
<i>GP_RBF</i>	77.6535	31.8452	25.0550	144.9610	9.0503
<i>SVM_NPoly</i>	77.6273	30.8465	24.9340	140.4480	8.7665
<i>SVM_Poly</i>	78.1905	32.2589	24.6800	140.8740	9.1679
<i>SVM_PUK</i>	77.7258	32.4119	25.0960	148.2740	9.2113
<i>SVM_RBF</i>	76.8083	31.7987	24.7750	144.1970	9.0371
<i>ANFIS_trimf</i>	77.6903	32.4814	24.9240	148.3726	9.2311
<i>ANFIS_trapmf</i>	77.6903	32.4809	24.9238	148.3908	9.2309

<i>DNN</i>	77.5436	31.5921	25.6160	141.4490	8.9784
	Testing data set				
<i>Actual</i>	78.5302	31.1486	30.0670	126.8940	13.8105
<i>LR</i>	81.6212	30.7287	35.4332	121.9902	13.6243
<i>GP_NPoly</i>	79.3013	33.9259	23.0280	139.0580	15.0419
<i>GP_Poly</i>	79.6543	35.0175	27.6530	145.4770	15.5259
<i>GP_PUK</i>	75.3196	25.6369	33.0560	118.2640	11.3668
<i>GP_RBF</i>	77.9311	33.6984	24.1620	136.6720	14.9411
<i>SVM_NPoly</i>	80.2911	32.7544	27.3840	135.5890	14.5225
<i>SVM_Poly</i>	82.6211	38.0259	26.5700	150.8530	16.8598
<i>SVM_PUK</i>	75.3948	25.8657	32.9780	118.9090	11.4682
<i>SVM_RBF</i>	77.2636	33.7499	24.9380	137.6190	14.9638
<i>ANFIS_trimf</i>	77.5472	46.4618	21.4416	190.4383	20.6000
<i>ANFIS_trapmf</i>	80.5862	38.4850	8.1752	155.1375	17.0633
<i>DNN</i>	78.7763	32.9154	29.4840	136.3170	14.5939

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Table 5. Single factor ANOVA results (variation among various groups)

<i>Source of Variation</i>	<i>SS</i>	<i>Df</i>	<i>MS</i>	<i>F</i>	<i>P-value</i>	<i>F-critical</i>	Insignificant <i>Variation among groups</i>
Between Actual and LR	105.099	1	105.099	0.109793	0.742027	4.072654	✓
Between Actual and GP_Npoly	6.541164	1	6.541164	0.006167	0.937777	4.072654	✓
Between Actual and GP_Poly	13.89938	1	13.89938	0.012656	0.910963	4.072654	✓
Between Actual and GP_PUK	113.3868	1	113.3868	0.13934	0.710816	4.072654	✓
Between Actual and GP_RBF	3.94741	1	3.94741	0.003749	0.951467	4.072654	✓
Between Actual and SVM_Npoly	34.10705	1	34.10705	0.033388	0.855894	4.072654	✓
Between Actual and SVM_Poly	184.0909	1	184.0909	0.15238	0.698244	4.072654	✓
Between Actual and SVM_PUK	108.1387	1	108.1387	0.131935	0.718256	4.072654	✓
Between Actual and SVM_RBF	17.64804	1	17.64804	0.016734	0.897691	4.072654	✓
Between Actual and ANFIS_trimf	10.62872	1	10.62872	0.006794	0.934701	4.072654	✓
Between Actual and ANFIS_trapmf	46.49769	1	46.49769	0.037937	0.846509	4.072654	✓
Between Actual and DNN	0.666414	1	0.666414	0.000649	0.979796	4.072654	✓

Sensitivity Analysis:

Sensitivity analysis was carried out to found the most influencing input variable in prediction of SU of soil mixed with tires waste material. For this investigation, DNN based model working best than other developed models using this data set, was used. Several training data were prepared by eliminating single input variable at a time from training data set and results were listed in the form of statistical parameters such as CC, RMSE and MAE for test data set. Results from Table 6 conclude that Specific gravity of tires (Gst) and Size of clay (S) are the most influencing input variables in predicting the SU of soil mixed with tires waste material in comparison to other input variables used in this study. The third essential parameter is vertical stress (VS) in prediction of SU of soil mixed with tires waste material using DNN based model.

Table 6. Results of sensitivity analysis based on DNN model

Sr. No.	Input arrangement								Removed variable	Output	DNN		
	VS	T	C	S	Gst	LL	PI	Gsc			CC	MAE	RMSE
1										SU	0.9736	6.1870	7.5319
2									Gsc	SU	0.9631	7.8501	9.7593
3									PI	SU	0.9727	7.6336	9.2462
4									LL	SU	0.9727	7.6336	9.2462
5									Gst	SU	0.0710	53.6063	61.6422
6									S	SU	0.0875	53.5979	61.6333
7									C	SU	0.9594	10.763	13.7904
8									T	SU	0.9714	7.1351	9.1026
9									VS	SU	0.4339	27.3105	32.2794

Conclusion:

The outcomes of direct shear tests indicate that the mixing of more than 27% crushed tire to the low plasticity cohesive soil doesn't decrease the shear strength in comparison to the related values of pure cohesive soil. In mixed cohesive soil with high plasticity, when the cursed tire content enhances the shear strength of specimens reduces. It can be concluded that mixed crushed tires with cohesive soil can be used in earth structures without significant reduction.

This paper examines the potential of LR, GP, SVM, ANFIS and DNN based models in predicting the SU of soil mixed with tires waste material. From the comparison of performance evaluation parameters, it has been found that DNN based model works better for this data set, in comparison to other aforesaid soft computing based models. Performance of Poly kernel function based models are better than other kernel function based models using SVM and GP approaches. Another major conclusion was that trapezoidal MFs based ANFIS model works better than triangular MFs based ANFIS model. Sensitivity investigation concluded that Specific gravity of tires (Gst), Size of clay (S) and vertical stress (VS) are the most crucial input variables in predicting SU of soil mixed with tires waste material in comparison to other input variables used in this study.

Conflict of interest

The authors declare that they have no conflict of interest

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