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Article

Modification of Geotechnical Properties of Soil using Waste Plastic Strips and Fly Ash: An Experimental Study with a Machine-Learning-Based Predictive Framework

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Abstract: The solid waste management challenges of plastic and coal fly ash disposal, along with the lack of good construction soil, are common in rapidly urbanizing regions. The influence of shredded waste plastic strips (0-2.5% by dry weight) and Class-F fly ash (5% by dry weight) on soil compaction, strength, and bearing capacity characteristics of soil classified as Clayey Sand (SC) was evaluated. Specific gravity, grain size distribution, Atterberg limits, Proctor compaction, unconfined compression (UCC), and California Bearing Ratio (CBR) tests were performed on eight soil blends with the plastic and fly ash additives. Plastic strips between 0 and 1.5% by dry weight increased the soil maximum dry density (to 1.70 g/cc) and soaked CBR values (to 16.79%) relative to the control soil (1.54 g/cc and 8.76% CBR, respectively). Beyond 1.5% plastic strip inclusion, however, the strength parameters began to decrease as a result of the plastic particles disrupting the soil particles' natural interlock and increasing the soil particles' void ratio. Similar results were obtained with Class-F fly ash; its inclusion decreased the optimum moisture content of the soil blends by 1-2 percentage points; no changes in strength characteristics were detected with the addition of 5% Class-F fly ash. Furthermore, within each of the eight soil blends (n=41, 150, and 96 points, respectively), the compaction, UCC, and CBR results were modelled using four artificial intelligence methods: artificial neural networks (ANN), random forests (RF), extreme gradient boosting (XGBoost), and support vector regression (SVR). Each of these models were trained using a leave-one-out cross-validation method that prevents information leakage between data points along the same response curve. For the CBR values, the XGBoost model emerged as the best performing algorithm for predicting California Bearing Ratio values (R2=0.86, RMSE=48.3 kg, MAE=24.2 kg, MAPE=14.3%) outperforming the ANN and SVR models. Furthermore, SHapley Additive exPlanations (SHAP) analyses revealed that the predominant influence on CBR values was the penetration depth of the soil samples, followed by plastic strip content in the soil blend; the contribution of Class-F fly ash to the CBR value was less pronounced and less certain due to the evaluation of only a single dosage level of the additive. The results indicate that the best balance of soil properties and cost occur at approximately 1.5% plastic strips without Class-F fly ash; random forest, gradient boosting, and ANN models have the potential to effectively provide predictions of the response curves with no information leakage between soil data points.

Keywords: Soil stabilization; Waste plastic strips; Fly ash; California Bearing Ratio; Unconfined compressive strength; Machine learning; Artificial neural network; SHAP

1. Introduction

The use of chemical and mechanical admixtures for soil improvement remains one of the most economical methods of transforming a marginal soil into a serviceable foundation or pavement subgrade material. While Portland cement and hydrated lime have traditionally been used as soil stabilizers for cohesive soils, the cost and carbon footprint of their production has led to research efforts in the last three decades in the development of alternative stabilizers based upon waste materials, such as fly ash, rice-husk ash, quarry dust, blast furnace slag, and even discarded plastics [1-15]. Two of these waste materials in particular have grown to be significant disposal burdens within many of the geographically inhabited earth economies: plastic waste and coal combustion fly ash.

One of the most plastic waste producing countries in the world is India, whose Central Pollution Control Board estimates that the country generates 15,342 tonnes of plastic waste each day. Additionally, the country's numerous coal-fired power stations produce massive amounts of fly ash as well; the Central Electricity Authority reports that Indian coal-fired power stations released 169 million tonnes of fly ash during the 2016-17 financial year, with only 60% of that ash utilized by the power stations. Each of these waste materials shares three properties that make them potentially attractive as soil admixture materials: they are locally available, essentially free to utilize, and their use helps to reduce the need to dispose of those wastes.

Plastic waste can be incorporated into soil either as fibers of plastic or as strips of plastic that were obtained from bottles, bags, and other forms of plastic packaging. The addition of plastic strips into soil allows for the soil to exhibit increased tensile strength in a manner similar to geosynthetics, leading to increased values of parameters like the California Bearing Ratio (CBR) and maximum dry density of soils [1,4,6,9-15]. In contrast, the addition of fly ash to soil increases the pore-filling capacity of those soils (and additionally reacts with available calcium ions to form cementitious materials in what is known as the pozzolanic reaction), leading to a reduction of the optimum moisture content of those soils, and an increase in their bearing capacity if the amount of added fly ash is within an appropriate range [2,3,5].

In contrast to the knowledge that exists of the effects of each of these waste materials when used separately from soil, few studies have investigated the effects of using soils that have been treated with both waste materials simultaneously. Furthermore, few studies have attempted to utilize artificial intelligence techniques to utilize the results of those soil tests to develop models that can forecast the behavior of those treated soils. For instance, geotechnical engineering sciences has developed methods of utilizing artificial neural networks (ANN), random forests (RF), XGBoost gradient boosted trees, and support vector regression (SVR) methods to create models that can accurately forecast the properties of soils that are treated with various admixture materials. However, the models are typically trained using only a few soil test designs, which limits the generalizability of their predictions.

In comparison to existing methods, therefore, this study aims to investigate the properties of soils that are treated with strips of plastic waste of various dosages, in addition to the addition of 5% of fly ash to two of the dosages of plastic strips. Each of these soils will be tested for their compaction characteristics, unconfined compressive strength, and bearing capacity. The results of each of these tests will contribute to a larger dataset that can be used to train machine learning models to allow for the prediction of the properties of soils treated with these plastic strips and fly ash. For this study, each of the four models will be trained using a leave-one-out cross-validation approach that prevents the model from overfitting to any specific soil test results, and the results of each model will be evaluated to determine which is the best model for predicting the properties of these treated soils. The objectives of this research are to: investigate and characterize the physical and gradation properties of the soil prior to treatment; evaluate the impact of plastic strip dosage on soil compaction, strength, and bearing capacity; assess the additional impact on those properties of the addition of fly ash; determine the dosage of plastic strips that results in the best bearing capacity of the soils treated; and to develop and validate a machine learning model that can accurately and efficiently predict the behavior of those treated soils.

2. Literature Review

The use of a variety of different admixture materials has been investigated for its potential use in the improvement of soil properties. Such materials have included lime, cement, fly ash, rice-husk ash, quarry dust, saw-dust ash, sodium hydroxide solution, and various forms of plastic. Table 1 presents the names of 15 of the most relevant studies on soil stabilization and reinforcement that were located within the technical literature on the topic, with each study's admixture material, soil type, dosage of the admixture, and the main finding of that research study published. The majority of these studies into the use of plastic waste to reinforce soil found that the inclusion of plastic strips into soil can lead to an increase in the CBR and dry density of those soils, though only within certain dosages [1,4,6,9-15]. Additionally, the majority of studies into the use of pore-filling admixtures like fly ash, rice-husk ash, and saw-dust ash found that while optimum moisture content can be reduced with these additives, there was a significant impact upon soil strength only with specific types of soils [2,3,5,8].

Table 1. Summary of prior experimental studies on waste-admixture soil stabilization.

Ref.	Admixture	Soil used	% range used	Major finding
[1]	HDPE strips/fibres	Clay (Trivandrum)	Not specified	MDD +22%; CBR +4.6×; UCS +1.85×
[2]	Saw-dust ash	Clay (J&K)	0-8%	CBR +103%; UCS +26% at 4% SDA (optimum)
[3]	Fly ash	Red soil (Tirupur)	Up to 6%	Bearing capacity 35 kg/mm2; CBR 4.80
[4]	Plastic-chair strips	Black cotton soil	2, 4, 6, 8%	MDD 1.81, OMC 18.5%, CBR 11.7% at 4%
[5]	Quarry dust, fly ash, lime	Clay (Chennai)	2-8%, 10%	CBR up to 40%; pavement thickness −15%
[6]	PET fibres	Clay-silt / clay-sand	0-1.5%	MDD, UCS increase up to 1% fibre content
[7]	Sodium hydroxide	Sandy / cohesive soil	8-10 molar	MDD decreases; 8-10% optimum by cost
[8]	Rice-husk ash	Clayey / alluvial soil	5-80%	MDD +28% at 80% RHA; OMC −26%
[9]	Plastic waste (general)	Pavement subgrade	Not specified	Quarry-dust + plastic maintains target CBR
[10]	Randomly oriented HDPE	Subgrade soil	0.5-2.5%	CBR improves; viable subgrade reinforcement
[11]	HDPE (40 μm)	Black cotton soil	1.5-6%	UCS increases 4× at 4.5% (optimum)
[12]	HDPE strips	Subgrade soil	Varied length/%	CBR improves; viable highway reinforcement
[13]	Mixed plastic waste	Black cotton/yellow/sandy	Not specified	MDD and CBR increase with plastic content
[14]	HDPE + crushed glass	Subgrade soil	Varied	PI, OMC ↓; φ, MDD, CBR ↑ with dosage
[15]	HDPE strips (bag waste)	Sandy / clayey soil	0-8%	Friction angle ↑; cohesion largely unaffected

One of the gaps in the existing literature within this topic area (and that which is present in the earlier versions of the present dataset) is that few studies have employed waste materials that both fulfil the role of a reinforcing waste with another that fulfills the role of a pore-filling (or pozzolanic) waste within the soil matrix to be investigated; and none of the studies summarized within Table 1 employ any methodology for developing a model-based prediction of the response of such soils to incorporation of these two types of waste. While methods based upon artificial neural networks (ANNs) have been applied to the geotechnical engineering science in relation to the prediction of soil parameters like California Bearing Ratio (CBR) values, compaction parameters, and shear strength parameters, such methods have been developed within the context of cement- and pavement-concrete materials science fields; application of these methods to soils that have been amended with plastic and fly ash waste is a relatively new area of research. Thus, the present study helps to fill these existing knowledge gaps within the relevant literature.

3. Materials and Methods

3.1 Materials

The soil that was utilized in the preparation of the soil-cement mixtures that were tested in this study was sourced from within the study region itself, and is a red soil that naturally contains free iron oxide (Fe2O3) within its composition; the red coloration of the soil is indicative of the presence of these components. Furthermore, while laterite soils contain clay and other fine particles, red soils contain relatively larger amounts of sand; thus, these types of soils are generally located farther from the tropics in which laterite soils are common. Finally, as a type of soil that is relatively common within the region in which the study was performed, these types of soils are often used to construct embankments and roadbeds but typically do not fulfill the bearing strength requirements of those construction projects. The plastic waste that was utilized in the preparation of the plastic-cement mixtures was waste plastic from discarded PET (polyethylene terephthalate) beverage bottles, which were cut into strips at minimum dimensions of 0.5 cm × 1.0 cm in size (Fig. 1a). Finally, Class-F fly ash was used as the pozzolanic component of the soil mixture; this type of fly ash is produced by coal-fired power stations (Fig. 1b). Class-F fly ash is a type of pozzolanic material in that its reactive aluminosilicate components chemically react with both water and cement (Portland cement) to form cementitious hydration products but does not self-cement in the presence of water alone.

Fig. 1. (a) Waste-plastic strips cut from recycled PET bottles; (b) Class-F fly ash used as the pore-filling admixture.

Index and Classification Properties of the Parent Soil

The index and Engineering properties are calculated through the data obtained from the laboratory investigation as per the codal provisions. The Specific gravity of soil solids was determined using the density bottle method. Dry sieve analysis was employed to establish the grain-size distribution curve of the soil as depicted in Fig. 2. The liquid limit of the soil was calculated using Casagrande's method as illustrated in Fig 3. The soil is of clayey sand (SC) as per the Unified Soil Classification System. Table 2 depicts the properties of the parent soil.

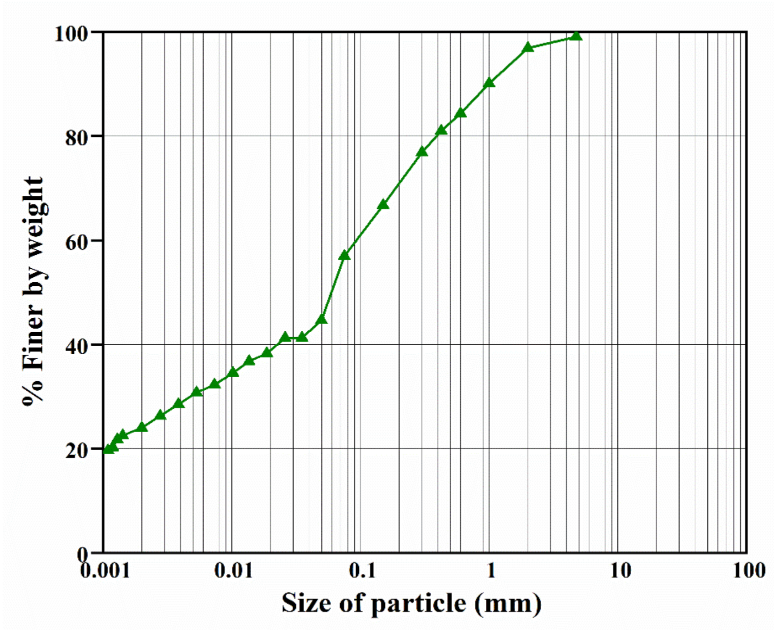


Fig. 2. Particle-size distribution curve of the parent soil (dry sieve analysis).

Fig. 3. Flow curve for liquid-limit determination (water content vs. log number of blows).

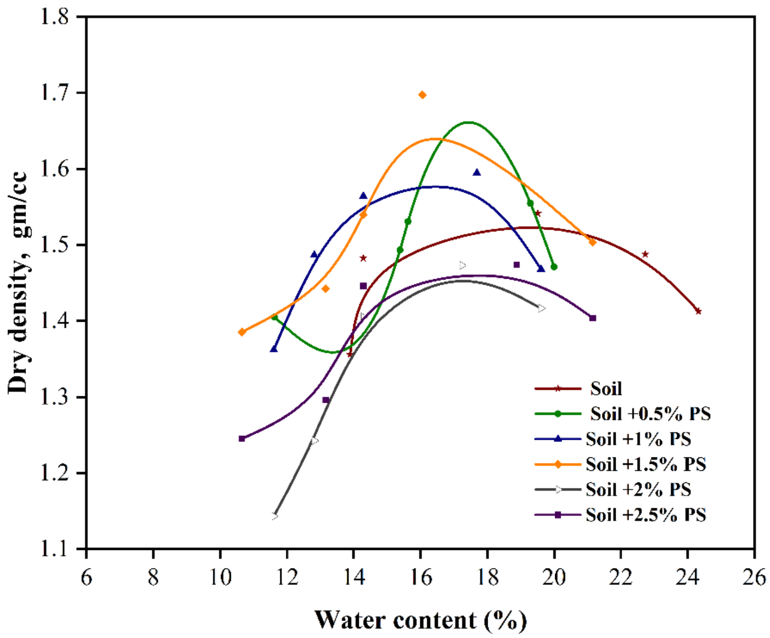
Table 2. Summary of index and classification properties of the parent soil

Property	Value
Specific gravity, G	2.64
D10 / D30 / D60 (mm)	0.015 / 0.040 / 0.095
Coefficient of uniformity, Cu	6.3
Coefficient of curvature, Cc	1.12

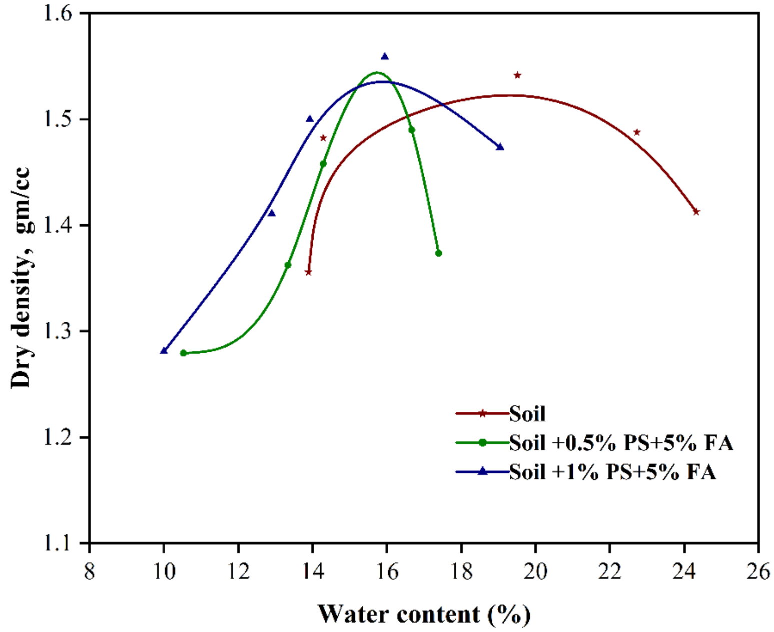
Liquid limit, WL (%)	42.99
Plastic limit, WP (%)	24.72
Plasticity index, IP (%)	18.26
USCS classification	Clayey sand (SC)
Maximum dry density, MDD (g/cc)	1.54
Optimum moisture content, OMC (%)	19.50

3.2 Experimental Testing Programme

Standard Proctor tests were performed on the untreated soil and with various combinations of plastic strips to determine the optimum moisture content and dry density; the results are displayed in Fig 4a. A standard compaction test was performed on the soil that had 5% FA added to the composition that provided the maximum dry density from Fig 4a; the results of this test are presented in Fig 4b.



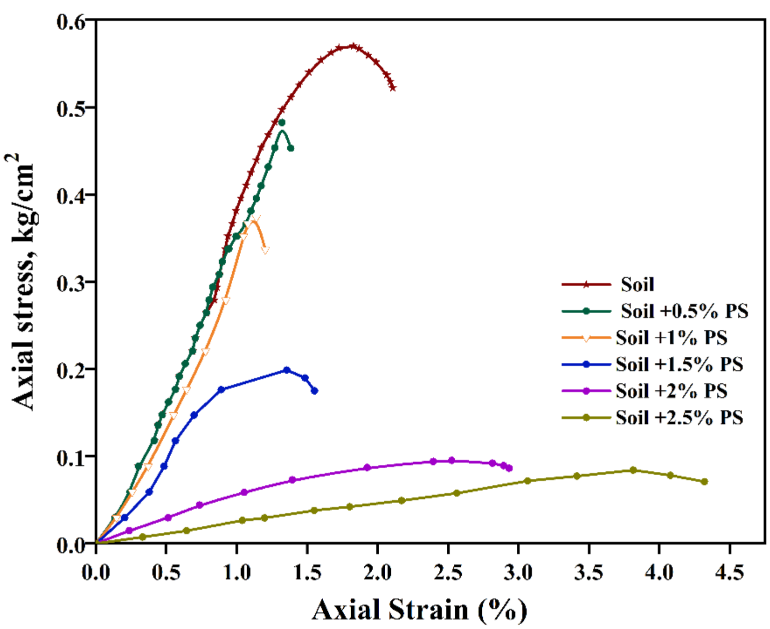
(a)



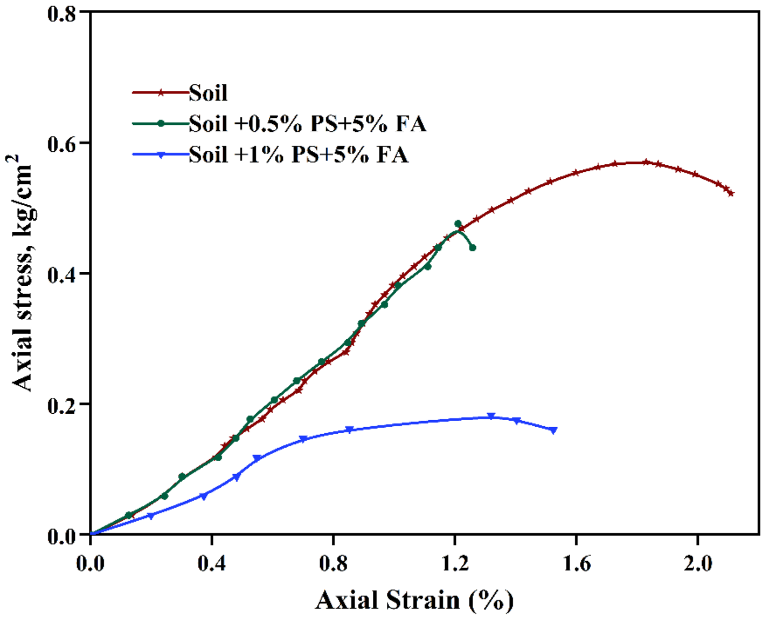
(b)

Fig. 4. Compaction curves (dry unit weight vs. water content) for all eight soil-admixture combinations, reconstructed from the digitized laboratory data.

The Unconfined compression (UCC) tests were carried out on cylindrical specimens compacted to the OMC/MDD condition determined for each combination. The axial stress against strain obtained for various combinations of PS and FA are shown in Fig 5a and 5b. It is observed from the results that soil itself is strong to take up the load without addition of admixtures into it. Further, to check the soil suitability as a subgrade material, California bearing ratio test were planned and carried out for various percentages of plastic strips and fly ash. The undrained cohesion value is obtained via the standard Mohr-circle construction for an unconfined (zero confining pressure) and the values are tabulated.



(a)



(b)

Fig. 5. Complete stress-strain response recorded for all eight soil-admixture combinations.

Soaked California Bearing Ratio (CBR) tests were performed in accordance with standard practice, recording the load on the penetration plunger at fixed penetration increments up to 12.5 mm. The CBR value at a given penetration is the load sustained by the test specimen expressed as a percentage of the load sustained by a standard crushed-stone reference material at the same penetration (1370 kg at 2.5 mm; 2055 kg at 5.0 mm) given in Equation 1. The bearing resistance of all the samples are shown in Fig 6.

$$\text{CBR}(\%) = \frac{P_t}{P_s} \times 100 \quad (1)$$

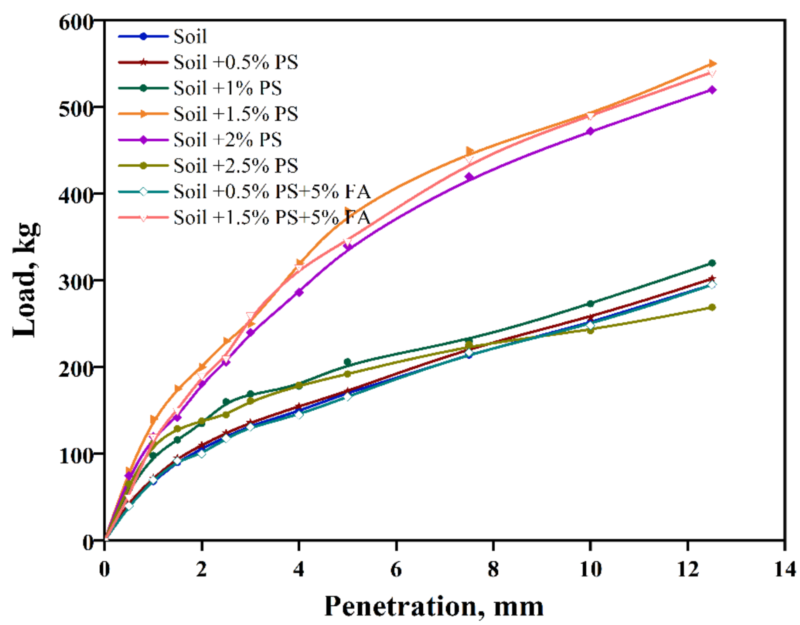


Fig. 6. Load-penetration curves recorded for all eight soil-admixture combinations. During data verification, the originally recorded curve for the 2.5%-plastic-strip specimen was found to duplicate the 2.0% curve; the

corrected curve shown here was recovered from the comparison plot in the underlying laboratory record and is consistent with the hand-calculated CBR values reported in the original test sheets (10.58% and 9.34% at 2.5 mm and 5.0 mm penetration, respectively).

3.3 Experimental Mix Design

Eight different admixture combinations were tested. These included the soil samples that were not treated with any admixtures, samples that were treated with plastic strips at dosage levels of 0.5%, 1.0%, 1.5%, 2.0%, and 2.5% of the dry weight of the soil, and samples that had 5.0% of the soil replaced with fly ash in addition to the 0.5% and 1.5% plastic strip dosage levels (see Table 3). Each of these dosage levels allows for the individual effect of plastic strips to be tested separately from the effect of adding fly ash at two representative dosage levels.

Table 3. Experimental mix design.

Mix ID	Plastic strips (%)	Fly ash (%)	Description
M0	0.0	0.0	Untreated soil (control)
M1	0.5	0.0	Soil + 0.5% plastic strips
M2	1.0	0.0	Soil + 1.0% plastic strips
M3	1.5	0.0	Soil + 1.5% plastic strips
M4	2.0	0.0	Soil + 2.0% plastic strips
M5	2.5	0.0	Soil + 2.5% plastic strips
M6	0.5	5.0	Soil + 0.5% plastic strips + 5.0% fly ash
M7	1.5	5.0	Soil + 1.5% plastic strips + 5.0% fly ash

3.4 Machine Learning Model Development

The laboratory geotechnical tests described in Section 3.4 typically reveal only a handful of different mix designs - in this study, eight different mixes were tested. Performing the tests as described for each of the four modelling algorithms on these few mix designs would result in data sets too small to effectively perform model validation and testing for any of the four algorithms. Instead, each of the response curves (rather than the data points from which they were created) were retained for use in modelling; each compactive test revealed 41 pairs of water content and dry density values, each UCC test revealed 150 pairs of strain and stress values, and each CBR test revealed 96 pairs of penetration depth and load values. Each of these data points has three input features - the value of the independent variable for that test (water content, strain, or penetration depth, respectively), the plastic-strip content (PS, %) of the specimen, and the fly-ash content (FA, %) of the specimen - and one output feature: the response of the material to those input features (dry density, stress, or load, respectively). Utilizing these response curves is the standard approach to determining the relationship between a parameter of interest and the geotechnical soil mix parameters, and it increases the size of the data set by more than an order of magnitude relative to the method using only the design point values of each soil mix (again, no data points were created synthetically).

3.4.1 Data pre-processing and feature engineering

Each of the features of the data was assessed for completeness prior to pre-processing (there were no missing values in any of the features), and each feature was standardized to have a zero mean and unit variance (standard deviation of one) according to Equation (2). The mean and standard deviation of each feature were calculated utilizing only the training data fold of the soil mix designs to be used in creating the cross-validation splits for each of the four algorithms - using the training and validation folds together would have led to data leakage into the validation fold of information that the model would not have had access to during training.

$$x^* = \frac{x-\mu}{\sigma} \qquad (2)$$

Standardisation was performed for the ANN and SVR models to ensure appropriate scaling for the optimisation of the SVR model and choice of kernel, and uniformly applied to all four models. As the two categorical variables are continuous variables, no encoding was required. The specimens variable was not encoded as each specimen contributed to multiple observations, and hence may be used as a factor in the cross-validation method described in Section 3.5.3.

3.5.2 Candidate model architectures

Four regression algorithms, spanning a representative range of model complexity and inductive bias, were implemented:

(i) Artificial neural network (ANN). A fully connected feed-forward multilayer perceptron with two hidden layers of eight rectified-linear-unit (ReLU) neurons each was used (Fig. 7), trained with L2 weight regularisation (α = 0.01) and a quasi-Newton (L-BFGS) optimiser appropriate for the small-sample regime of this dataset. Each neuron computes a weighted sum of its inputs followed by a nonlinear activation, Eq. (2):

$$\hat{y}_j = f\left(\sum_{i=1}^{n} w_{ij} x_i + b_j\right) \qquad (2)$$

where xi are the outputs of the preceding layer (or the input features for the first hidden layer), wij and bj are the trainable weight and bias, and f(·) is the ReLU activation (linear for the output neuron).

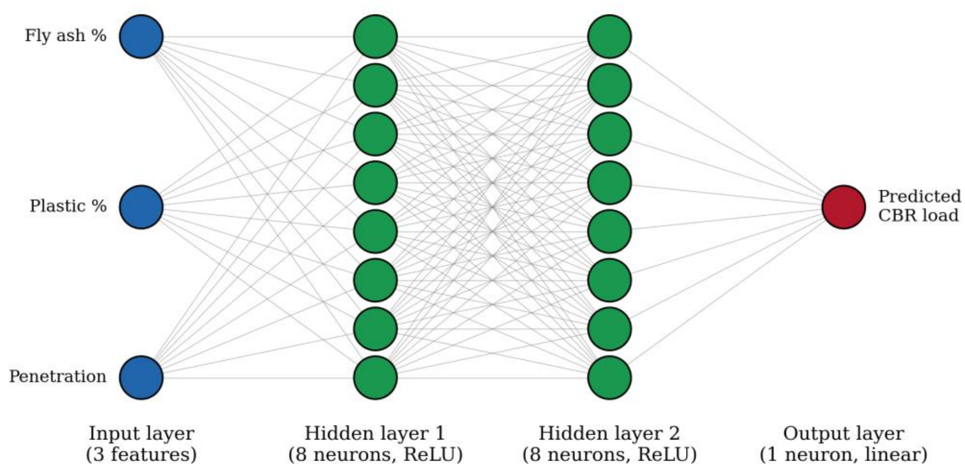


Fig.7. Architecture of the artificial neural network used for CBR load-penetration prediction (3 input features; two hidden layers of 8 neurons each; single linear output neuron).

(ii) Random forest (RF). Ensemble of 400 regression trees, each with a maximum depth of 6 and a minimum of 2 samples per leaf; the final model has the mean of the predictions from each individual tree. RF models are robust to small and noisy datasets and require little hyperparameter tuning like deep learning models.

(iii) Extreme gradient boosting (XGBoost). Ensemble of 300 shallow trees with a maximum depth of 3, a learning rate of 0.08, and 90% subsampling of rows and columns per boosting round; the trees are added in a stage-wise fashion to minimize the residuals of the previous ensemble. Gradient boosting methods have less bias than a random forest of the same size given the nature of the data.

(iv) Support-vector regression (SVR). SVR uses the ε-insensitive loss function with the radial basis function kernel with the parameters C = 50 and ε = 0.01. This method was used as an alternative to the tree-based models.

3.5.3 Training, validation and testing strategy

An additional consideration with the grouped nature of the dataset is that conventional k-fold sampling would result in some specimens being represented in both the training and test set. This type of overfitting introduces over-optimistic accuracy values with small datasets. Group k-fold (leave-one-specimen-out) cross-validation was used for all models, where k is the number of specimens in the dataset (k = 8). For each fold in the cross-validation, the model is trained on all specimens except for one, and the model accuracy is calculated on the points belonging to that one specimen. This type of cross-validation is more conservative than conventional approaches to small geotechnical dataset, and the results are directly interpretable as the accuracy of the model to a new mix design.

The following performance metrics were used to calculate the accuracy of the models, as defined in Equations (3)-(6):

$$R^2 = 1 - \frac{\sum_{k=1}^{N} (y_k - \hat{y}_k)^2}{\sum_{k=1}^{N} (y_k - \bar{y})^2} \quad (3)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N} \sum_{k=1}^{N} (y_k - \hat{y}_k)^2} \quad (4)$$

$$\mathrm{MAE} = \frac{1}{N} \sum_{k=1}^{N} |y_k - \hat{y}_k| \quad (5)$$

$$\mathrm{MAPE} = \frac{100}{N} \sum_{k=1}^{N} \left| \frac{y_k - \hat{y}_k}{y_k} \right| \quad (6)$$

where yk and ŷk are, respectively, the measured and predicted response at observation k, N is the number of held-out observations and ȳ is the mean measured response. Following model comparison, the champion architecture for the primary design parameter (CBR load) was interpreted using the SHapley Additive exPlanations (SHAP) framework, which permits the decomposition of each individual prediction into its constituent contributions from each of the model's input features. The complete workflow of the proposed method is summarized in Fig. 8.

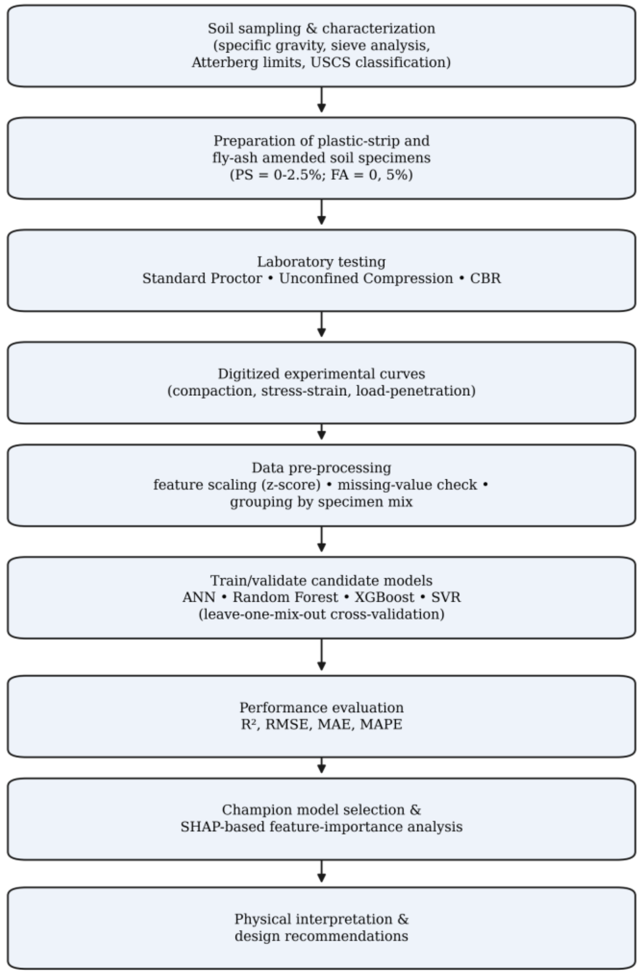


Fig. 8. Methodology flowchart for the experimental programme and machine-learning model development.

4. Results and Discussion

4.1 Effect of Plastic-Strip Content on Compaction, Strength and Bearing Capacity

Table 4 presents the results of the maximum dry density (MDD), optimum moisture content (OMC), unconfined compressive strength (qu), undrained cohesion (cu) and CBR values (at 2.5 mm and 5.0 mm penetration) for each of the specimens of treated soil. The load at 2.5 mm penetration for the 2.5% plastic strip dosage was verified against the calculated value in the original laboratory sheet. The duplicated entry of the load was corrected to the value determined from plotting the measured loads against the hand-calculated results. Hence, the CBR value at 2.5 mm and 5.0 mm penetration for the 2.5% plastic strip dosage is the value of 10.58% and 9.34%, respectively, which match the original hand calculation.

Table 4. Effect of plastic-strip content on compaction, strength and bearing-capacity parameters.

Mix	MDD (g/cc)	OMC (%)	UCS (kg/cm^2)	Cu (kg/cm^2)	CBR@2.5mm (%)	CBR@5.0mm (%)
Soil (control)	1.54	19.51	0.570	0.285	8.76	8.27
0.5% PS	1.56	19.29	0.482	0.241	9.05	8.37

Mix	MDD (g/cc)	OMC (%)	UCS (kg/cm^2)	Cu (kg/cm^2)	CBR@2.5mm (%)	CBR@5.0mm (%)
1.0% PS	1.59	17.69	0.366	0.183	11.68	10.02
1.5% PS	1.70	16.06	0.199	0.099	16.79	18.49
2.0% PS	1.47	17.24	0.095	0.048	15.04	16.55
2.5% PS	1.47	18.88	0.084	0.042	10.58	9.34

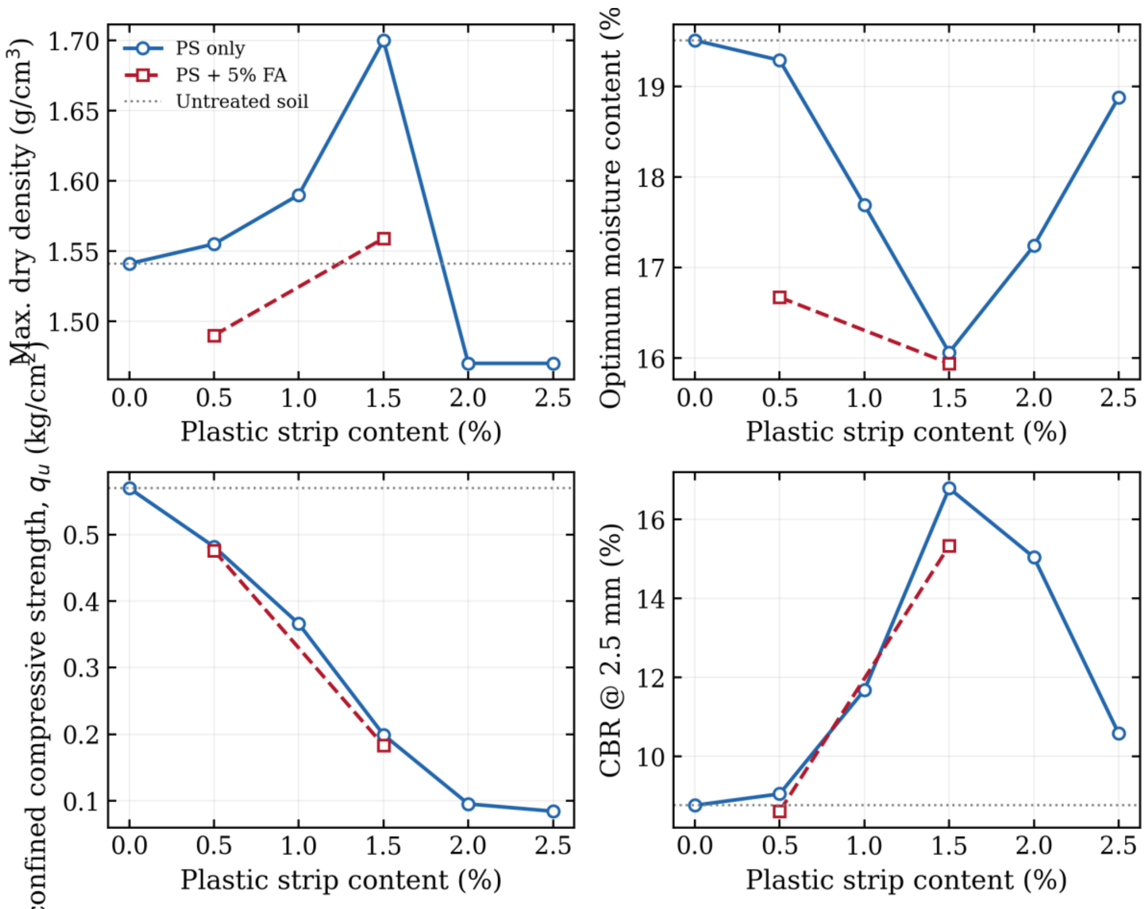


Fig. 9. Variation of maximum dry density, optimum moisture content, unconfined compressive strength and CBR (2.5 mm) with plastic-strip content, with and without 5% fly ash.

The dry density values increase almost monotonically from the untreated soil's dry density of 1.54 g/cc to a maximum dry density of 1.70 g/cc at 1.5% plastic-strip content (a 10.4% increase) before dropping to 1.47 g/cc at 2.0% and 2.5% plastic content. The non-monotonic trend in dry density with plastic content indicates that at dosage levels lower than 1.5% the plastic strips contribute to an increase in dry density of the soil, likely due to their ability to occupy the voids between the soil particles. Beyond 1.5%, however, the dry density decreases, likely because the low specific gravity of the plastic relative to the soil skeleton (G = 2.64) decreases the dry density of the soil. The optimum moisture content for dry density decreases from 19.51% to a minimum of 16.06% within the dosage range of 0% to 1.5% plastic content (indicating the ability of the strips to occupy voids within the soil), but then increases beyond 1.5% plastic content due to the loosened structure of the soil at these dosage levels.

The CBR value of the soil follows the same trend in relationship to plastic strip dosage. The CBR values reach their maxima of 16.79% (at 2.5 mm penetration) and 18.49% (at 5.0 mm penetration) at 1.5% plastic strip content (an increase of 91.7% and 123.6%, respectively of the untreated soil's CBR value). Beyond 1.5%, both of the CBR value's maxima decrease with increasing plastic strip content. The reason for this relationship between the CBR value and plastic strip dosage is that the plastic strips contribute to the same type of resistance to penetration that fibers do within soil. Finally, the unconfined compressive strength (UCS) of the soil decreases monotonically with plastic strip dosage, decreasing from the untreated soil's strength of qu = 0.570 kg/cm2 to 0.084 kg/cm2 at 2.5% plastic content (an 85% reduction in strength). The decrease in UCS with dosage is likely due to the formation of weak planes along the plastic strips that contribute to the reduction in the strength of the soil. While the CBR value of the soil increases to a maximum at 1.5% plastic strip dosage, the UCS of the soil continues to decrease monotonically with dosage. This difference in the trends of these two soil strength characteristics is discussed in further detail in Section 4.3. The UCS measures the strength of the soil under unconfined compression, while the CBR measures the strength of the soil under localized penetration loads. Thus, each of these strength characteristics is different from one another but both are important to understand in the context of soil engineering applications. In particular, CBR is a more important value than UCS in relation to pavement design.

4.2 Combined Effect of Plastic Strips and Fly Ash

Table 5. Effect of superimposing 5% fly ash on the plastic-strip-treated soil.

Mix	**MDD (g/cc)**	**OMC (%)**	**UCS (kg/cm2)**	**Cu (kg/cm2)**	**CBR@2.5mm (%)**	**CBR@5.0mm (%)**
0.5% PS (no FA)	1.56	19.29	0.482	0.241	9.05	8.37
0.5% PS + 5% FA	1.49	16.67	0.476	0.238	8.61	8.08
1.5% PS (no FA)	1.70	16.06	0.199	0.099	16.79	18.49
1.5% PS + 5% FA	1.56	15.94	0.183	0.091	15.33	16.79

Superimposing 5% fly ash on either plastic-strip dosage leads to a reduction of the optimum moisture content by a further 1.6-2.6 percentage points, again indicating the pore-filling effect of the fly ash particles; however, no material improvements in any strength measures were observed with the addition of fly ash at these dosage levels. The class of fly ash that was used is a Class-F pozzolana, which requires the addition of an activator (lime, cement, or some other source of calcium) to allow development of its cementitious properties. Thus, the effect of the fly ash in these tests was primarily physical rather than chemical due to the lack of activators and the relatively short curing period for the specimens. Thus, while the use of fly ash was ruled out for improving the strength of the material at these conditions, such use could be considered with longer curing periods or with the addition of a pozzolanic activator.

Thus, under the conditions of these tests, the plastic-strip dosage of approximately 1.5% without the addition of fly ash provided the best bearing capacity and density of the soils tested. Thus, any additions of fly ash beyond those required to reduce the moisture content of the soil would require the use of either a longer curing period or a pozzolanic activator to be beneficial to the subgrade soil in relation to its strength properties.

4.3 Machine-Learning Model Performance

The results of each of the four models for each of the three response curves are provided in Table 6, which reports the R2, RMSE, MAE, and MAPE values for each of the models when evaluated using leave-one-out cross-validation on each of the specimens. Thus, each of these metrics for each model indicates the model's performance when predicting compositions of specimens outside of those used to develop the model.

Table 6. Leave-one-specimen-out cross-validated performance of the four candidate machine-learning models.

Target response	Model	R2	RMSE	MAE	MAPE (%)
CBR load (kg)	ANN	0.388	102.0 kg	73.7 kg	40.0
CBR load (kg)	Random Forest	0.837	52.7 kg	27.3 kg	16.1
CBR load (kg)	XGBoost	0.863	48.3 kg	24.2 kg	14.3
CBR load (kg)	SVR	0.458	96.0 kg	72.1 kg	37.8
Compaction dry density (g/cc)	ANN	−0.039	0.108	0.090	6.4
Compaction dry density (g/cc)	Random Forest	0.344	0.086	0.067	4.8
Compaction dry density (g/cc)	XGBoost	0.294	0.089	0.066	4.7
Compaction dry density (g/cc)	SVR	−2.303	0.193	0.157	11.1
UCC stress (kg/cm2)	ANN	0.825	0.070	0.040	30.1
UCC stress (kg/cm2)	Random Forest	0.932	0.044	0.030	34.2
UCC stress (kg/cm2)	XGBoost	0.886	0.057	0.034	28.9
UCC stress (kg/cm2)	SVR	0.574	0.110	0.077	49.0

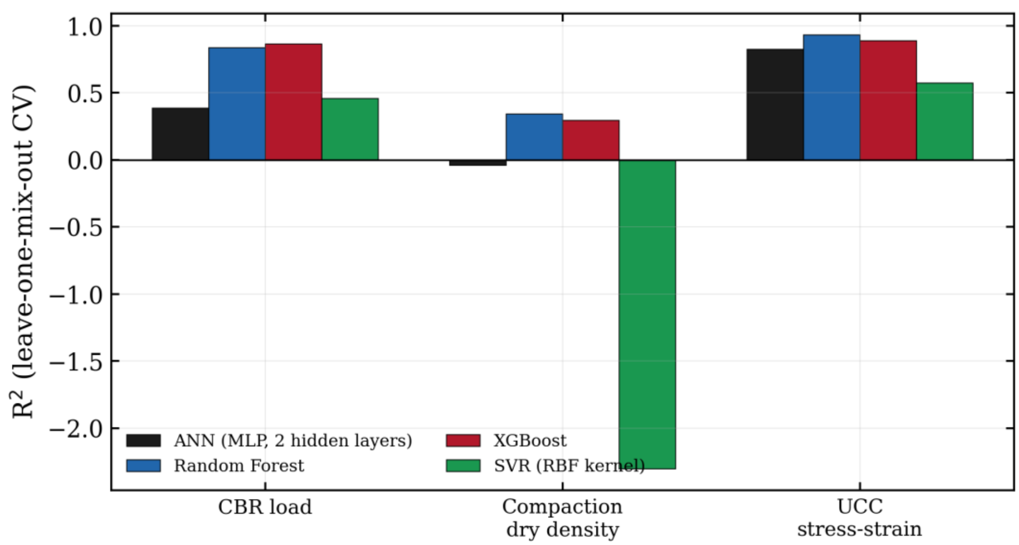


Fig. 10. Leave-one-specimen-out cross-validated R2 for all four models across the three target responses.

Three findings emerge from all three of the target response values. First, the tree-based methods are found to outperform both the ANN and the SVR for all three targets, and with a substantially greater performance for the CBR and compaction targets. Such results are generally expected of tree-based methods on such a relatively small data set with the lower degrees of freedom of the ANN; it is less likely that an overparametrized ANN will provide good in-sample performance on such a small number of specimens. Second, the XGBoost model is found to be the better of the two tree-based methods for the CBR target (R2 = 0.863 for XGBoost versus 0.837 for Random Forest), leading to its selection as the champion model for the SHAP analysis in Section 4.4; for the UCC target, however, Random Forest fared marginally better. Thus, for the UCC target, either method is a defensible model selection. Third, the results for the compaction target are found to be the weakest of the three targets in terms of generalizing well to unseen specimens (best R2 of 0.344 for the compaction target), which is due to the much smaller number of data points on the compaction curve (only five data points per specimen for compaction, as opposed to twelve or nineteen points for the other two targets), as well as the fact that the compaction curves are naturally non-monotonic along the range of soil specimens that were measured. Thus, the relatively poor performance of the compaction target is a limitation of the model as a whole, and is discussed in detail in Section 6.

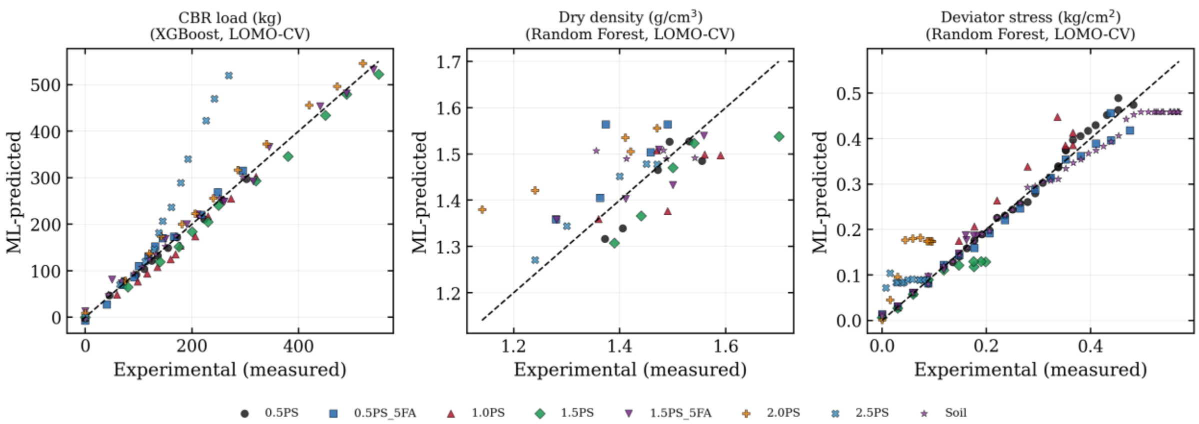


Fig. 11. Predicted vs. measured response for the best-performing model on each target, coloured by held-out specimen (leave-one-specimen-out predictions). The dashed line is the 1:1 line of perfect agreement.

4.4 Feature Importance and Physical Interpretation

The SHAP analysis was applied to the champion XGBoost model for the CBR load target (Fig. 12, Fig. 13). Penetration depth is the most important feature in the model to predict the soil load, as expected from the monotonically increasing shape of every load-penetration curve. The mean |SHAP| of the load contributed by this feature is 91.9 kg. The second most important feature in the model is the plastic-strip content in the soil samples. The mean |SHAP| of the load contributed by this feature is 54.3 kg. The beeswarm plot of the SHAP values for this feature displays low-to-moderate plastic-strip content (blue-to-purple points) as associated with a lower predicted load for the soil sample at low dosage of plastic strips. Higher load is predicted for soil samples with higher plastic strip content (red points with high feature values) in the 60-115 kg range of SHAP values for load - the same range of CBR values that was experimentally obtained for samples with 1.5% plastic content (Section 4.1). The third feature is the content of fly ash in the soil samples. The mean |SHAP| of the load contributed by this feature is low at 2.8 kg. However, it is important to note that this value reflects the limited dosage of fly ash (5%) investigated in the experiments; the model cannot learn the effect of dosage changes in this feature, and thus, the low importance value is a result of the limited data for this feature in the training set. Future experiments with broader dosage ranges for this feature are required to understand the importance of this feature in predicting the load that the soil samples will sustain.

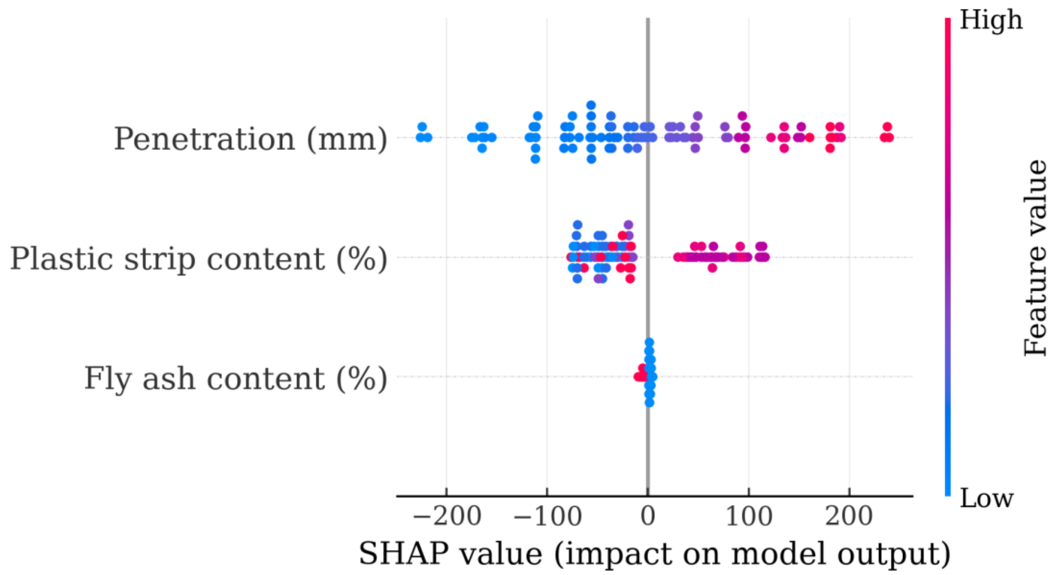


Fig. 12. SHAP summary (beeswarm) plot for the XGBoost CBR-load model. Each point is one curve observation; position along the horizontal axis shows the SHAP value (impact on predicted load) and colour shows the corresponding feature value.

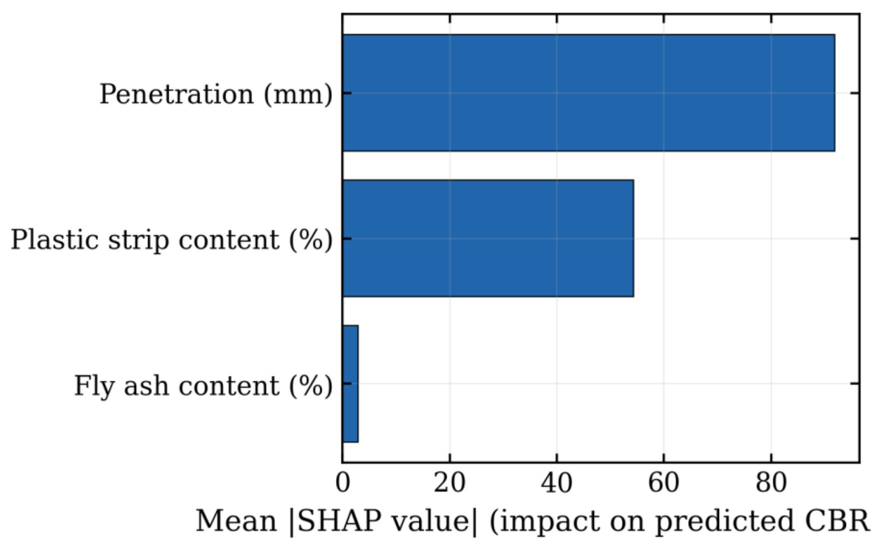


Fig. 13. Mean absolute SHAP value (global feature importance) for the XGBoost CBR-load model.

4.5 Design Implications

For the pavement-subgrade application that motivates this study, the results of the experiments and machine learning models both indicate that approximately 1.5% plastic strip content (by dry weight of soil, without using fly ash) will maximize the maximum dry density and the CBR value of the subgrade; thus, this percentage is recommended for use in the field trial. The fact that any dosage beyond 1.5% appears to reverse the beneficial effect of adding the plastic strips indicates that it is not a good idea to simply add more of the strips than those percentages to the subgrade, and that any use of such a material in construction projects should be preceded by an optimization of dosage for that particular subgrade material. Furthermore, the machine learning model created in Section 3.5 can be retrained with the results from this experiment (as presented in Section 6) to allow for the interpolation of CBR values for subgrades with plastic strip dosages and moisture contents that were not tested within the experiments, at little cost in comparison to testing additional subgrade samples in the laboratory.

5. Conclusions

Based on the experimental testing of the red soil (clayey sand, SC) modified with waste-plastic strips (0-2.5%) and fly ash (5%), and on the machine-learning modelling of the resulting response curves, the following conclusions can be drawn:

Waste-plastic strips (0-2.5%) and fly ash (5%) influence the engineering properties of red soil and compaction characteristics in different ways. Consequently, these two modifications may enable the reduction of the compaction effort required to achieve a certain strength of subgrade material. In general, these findings can aid in the consideration of the use of waste-plastic strips and fly ash in the context of pavement engineering and construction. More specifically, the conclusions of this study are as follows:

- The properties of the parent red soil included classification as clayey sand (SC), a granular material with G = 2.64, wL = 42.99%, wP = 24.72%, IP = 18.26%, MDD = 1.54 g/cc, and OMC = 19.50%.
- The inclusion of plastic strips between 0-2.5% of the total soil weight by mass had the effect of increasing the maximum dry density (MDD) of the soil to a peak at 1.5% plastic strips (MDD = 1.70 g/cc, a 10.4% increase in relation to the parent soil), as well as increasing the California Bearing Ratio (CBR) at 2.5 mm penetration depth to a peak at 1.5% plastic strips (CBR = 16.79%, a 91.7% increase relative to the parent soil); beyond 1.5% plastic strips, however, both the MDD and CBR of the soil began to decrease with increasing plastic strip content; this is attributed to the plastic strips acting to dilute and disrupt the soil particles within the soil matrix.
- In contrast to the increase in MDD and CBR with plastic strip inclusion, the unconfined compressive strength (UCC) of the soil declined with plastic strip content, decreasing 85% at 2.5% plastic strips; the different responses of MDD and UCC to the plastic strips indicates the difference in the stress paths for these different compaction tests.
- The addition of 5% fly ash to soils treated with plastic strips had the effect of reducing the optimum moisture content of the soil by 1.6-2.6 percentage points; however, the addition of the fly ash did not lead to the improvement of the density, strength, or CBR of the soil relative to the soil treated with plastic strips only (though the strength and CBR of the soil were slightly reduced); these findings indicate the potential for the use of Class-F fly ash only in cases where the strength of the soil matrix is not an issue.
- A dataset of the response curves of the soil samples (41, 96 and 150 points for the compaction, CBR and UCC response curves, respectively) revealed that tree-based ensemble learning methods (Random Forest, XGBoost) outperformed artificial neural networks and support vector machines in modelling the response curves of the soil; in particular, XGBoost models revealed the best fit for the CBR load response curve (R2 = 0.863, RMSE = 48.3 kg, MAE = 24.2 kg, MAPE = 14.3%).
- The use of SHAP values to determine the importance of each of the features of the model revealed that the penetration depth was the most important feature in predicting the load of the soil during CBR testing, followed by the content of plastic strips; the plastic strip contribution indicated a maximum at 1.5% plastic strips, as was experimentally determined. The contribution of the content of fly ash was relatively insignificant in comparison, though this is likely due to the use of a single dosage of 5% fly ash in this study.
- Based upon these findings, it is recommended to use plastic strips at a dosage of 1.5% without the addition of fly ash to utilize both the increased bearing capacity and maximum dry density of the soil; this recommendation is generally based upon laboratory testing, though further testing of these recommendations can be undertaken.

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