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Prediction of Deep Cement Column Strength for Pavement Improvement Using Machine Learning Models

Ahmad Safuan A Rashid[1] · **Ali Dehghanbanadaki**[2,3] · **Iman Golpazir**[3,4] · **Shervin Motamedi**[2]

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Abstract

This study introduces a machine learning (ML) approach to predict the required undrained shear strength of Deep Cement Mixed (DCM) (C_{uc}) columns used in pavement foundations. It presents a data-driven design method as an alternative to traditional techniques for estimating DCM column strength, marking a shift in geotechnical design practices. For this, two experimental datasets from laboratory investigations of soft soil improvement were combined to create a training database. To overcome limited experimental data, SMOTE-like interpolation methods were used to expand the database while maintaining geotechnical accuracy. Using the Pycaret library, a thorough analysis of different regression algorithms identified four top models: *Gradient Boosting Regression* (gbr), *AdaBoost* (ada), *Random Forest* (rf), and *Extra Trees* (et), with gbr showing the best performance ($R^2 = 0.965$, MSE=6.21 kPa). A sensitivity analysis of the models showed that ultimate bearing capacity (q_u) was consistently the most influential parameter (41–53%), followed by the undrained shear strength of the surrounding soil (C_{us}) at 18–31%. This suggests that enhancing soil strength before installing DCM may be more effective than simply increasing the area improvement ratio or column size. The model was packaged into a deployable pipeline to allow practical use by engineers, bridging the gap between advanced computational modelling and real-world geotechnical design of DCM-enhanced pavement foundations.

Keywords Deep cement mixed columns · Gradient boosting regression · Machine learning · Pavement foundation design · Undrained shear strength

✉ Ali Dehghanbanadaki
dehghanbanadaki.a@iau.ac.ir

✉ Iman Golpazir
I.golpazir@iau.ac.ir

Ahmad Safuan A Rashid
ahmadsafuan@utm.my

Shervin Motamedi
ac5172@coventry.ac.uk

1 Department of Geotechnics and Transportation, Faculty of Civil Engineering, Universiti Teknologi Malaysia, 81310 Johor Bahru, Johor, Malaysia

2 Department of Civil Engineering, Dmv.C, Islamic Azad University, Damavand, Iran

3 Research Center of Concrete and Soil, Dmv.C, Islamic Azad University, Damavand, Iran

4 School of The Environment, Coventry University, Coventry CV1 2LT, UK

Abbreviations

DCM	Deep Cement Mixed.
C_{uc}	Undrained shear strength of the column.
C_{us}	Undrained shear strength of the soil.
q_u	Ultimate bearing capacity.
L	Length of the column.
D	Diameter of the column.
A.I	Area improvement ratio.

1 Introduction

Deep Cement Mixing (DCM) columns are highly effective in improving the bearing capacity of embankments founded on soft soils. By creating a grid of strong, cemented columns within the weak ground, DCM columns significantly increase the overall shear strength of the foundation [1–6]. This reinforced soil mass provides a significantly more robust platform capable of supporting the substantial vertical stresses imposed by the embankment load, effectively preventing bearing capacity failure beneath the structure [7–9]. DCM columns can be installed in various patterns to optimise ground improvement for specific embankment loading conditions. Single columns may be employed strategically under localised high-stress areas, while group patterns are more common for widespread improvement beneath embankments. These group arrangements can include linear walls to resist lateral spreading, grid patterns (such as square or triangular layouts) to provide uniform bearing support and distribute vertical loads effectively, or block patterns that create a large, solid mass for maximum stiffness and bearing capacity enhancement under the entire embankment footprint. The choice of pattern directly influences the load transfer mechanism and the overall shear resistance provided by the improved ground [10, 11].

DCM columns can be designed to function in two primary conditions based on their interaction with the underlying soil layers: end-bearing and floating. End-bearing columns extend through the soft soil to rest on a firm, underlying stratum, directly transferring embankment loads to this competent layer. In contrast, floating columns terminate within the soft soil deposit itself, deriving their capacity from the shear resistance mobilised along their shafts and the improved strength of the composite soil-column mass. Particularly in scenarios involving deep soft soil deposits beneath embankments, where reaching a firm layer is impractical or uneconomical, DCM columns are often designed as floating elements [12]. This floating configuration proves particularly useful for supporting road infrastructure and embankments over soft ground, leading to its widespread adoption in numerous geotechnical projects worldwide [13, 14].

Besides the DCM columns, stone columns represent another widely adopted ground improvement technique with comparable applications in geotechnical engineering. Both methods create a composite foundation system in which vertical loads are partially transferred through columnar elements, enhancing bearing capacity and reducing settlement in weak soils [15]. However, while stone columns utilise compacted granular aggregate, DCM columns incorporate cement binders mixed with in-situ soil to develop semi-rigid elements with significantly higher cohesive strength [16]. This fundamental material difference influences their performance characteristics. DCM columns typically demonstrate superior effectiveness in reducing final settlements. In contrast, stone columns enhance consolidation rates because of their high permeability, leading to greater settlements during construction while minimising settlements after construction. The environmental impact also differs substantially between these techniques, with stone columns generally having a smaller carbon footprint compared to the cement-intensive DCM process. Nevertheless, DCM technology benefits from extensive implementation knowledge and documented success across numerous geotechnical applications [17]. The selection between these methods ultimately depends on project-specific priorities, including settlement tolerance, construction timeline constraints, environmental considerations, and soil conditions, with factors such as permeability and preconsolidation pressure (reflected in OCR values) being particularly influential on performance outcomes. Both techniques continue to serve complementary roles in geotechnical practice, offering engineers flexible options for addressing challenging ground conditions [17].

For embankments supported by floating DCM columns, the resulting increase in bearing capacity is significantly influenced by several interacting parameters. The inherent shear strength of the surrounding soft soil dictates its ability to support the columns and contribute to the overall system stability. A critical design parameter is the area improvement ratio (often denoted as a or A_r), representing the proportion of the plan area occupied by the columns relative to the total treated area; a higher ratio generally yields a greater capacity enhancement. Additionally, the load-bearing capacity of individual columns, as well as their role in enhancing the composite ground strength against bearing failure, is directly influenced by the shear strength properties of the column material, which are defined by its cohesion, friction angle, or undrained shear strength [18, 19].

Conventional binders employed in DCM techniques typically consist of Ordinary Portland Cement (OPC) Type B blast furnace slag cement. Nevertheless, specialised cementitious binders are sometimes used, primarily due to their economic viability, operational flexibility, and inherent robustness. For instance, achieving delayed stabilisation or enhanced long-term strength often involves strategically modifying binder compositions through the controlled addition or proportioning of supplementary materials, such as lime [20, 21], fly ash [22, 23], and gypsum [24], alongside the primary cementitious binder. Such binders are characterised by comparatively modest initial strength development, followed by significant strength enhancement over protracted timeframes [18]. Moreover, the amount of cement plays a crucial role in the development of strength in the treated soil composite. Typically, a higher cement content leads to improved column strength; however, this effect is limited beyond a specific threshold. Empirical observations suggest that beyond a cement content of approximately 25%, further additions yield only minimal increases in strength development [19, 25].

It is essential to recognise that the geotechnical characteristics of the native soil significantly influence the effectiveness of the stabilisation process. For instance, the response of peat, often encountered in soft ground conditions, differs considerably from that of clayey soils, although DCM techniques are adapted for both types of soil. Due to its characteristic, highly organic and hollow structure, peat stabilisation often requires the incorporation of filler materials in addition to cement [26]. Distinct from the requirements for clayey soils, effective stabilisation of peat typically involves initial cement contents between 100 and 200 kg/m^3. Nevertheless, the precise optimal dosages of cement and water are dictated by site-specific factors, namely the inherent characteristics and composition of the in-situ peat [27].

Conventional analytical and empirical methods for estimating DCM column strength often rely on simplifying assumptions and limited experimental data, which can restrict their accuracy and adaptability to diverse field conditions. There remains a critical need for more flexible, data-driven predictive tools that can integrate complex, non-linear interactions among geotechnical variables. Numerical modelling, such as FEM [28–32] and ML [33, 34], offers such capabilities by leveraging patterns in experimental data to improve prediction accuracy, reduce reliance on oversimplified models, and enable rapid design iterations for practical engineering applications. The successful application of various ML models across diverse geotechnical engineering domains, such as soil property characterisation, foundation settlement prediction, and slope stability analysis, has been well-documented in recent literature [35–43]. Encouragingly, ML methods have also demonstrated considerable promise in modelling the behaviour and predicting the performance of column-like geotechnical elements [44, 45].

Previous research has extensively explored the application of various ML methodologies to estimate the ultimate bearing capacity of foundations improved with column-like elements, such as stone columns and DCM columns, arranged in diverse patterns. These studies typically incorporated key geotechnical parameters as input features, including the area improvement ratio, the shear strength properties of the surrounding soft soil, and the mechanical characteristics of the columns themselves, with the ultimate bearing capacity serving as the primary predictive target. However, addressing a distinct yet critical aspect relevant to practical geotechnical design, this investigation diverges from prior approaches. The central objective of this study is to develop and evaluate ML models capable of estimating the required strength characteristics of DCM columns needed to achieve a specified target ultimate bearing capacity for an embankment foundation. Consequently, in this novel framework, the desired q_u is treated as an input parameter alongside other relevant geotechnical properties. At the same time, the necessary DCM column strength becomes the target output variable for the ML models. The methodologies employed, including the collation and merging of datasets, the selection and implementation of ML algorithms, and the application of data augmentation techniques where appropriate, are discussed in detail in the subsequent sections.

2 Experimental Datasets

The foundation dataset for the current ML investigation was meticulously compiled from two distinct experimental studies: the work by Rashid [46], designated herein as Dataset-1, and research conducted by Dehghanbanadaki et al. [47], referred to as Dataset-2. Both source datasets were derived from 1-g physical model experiments that investigated the behaviour of soft ground enhanced with DCM columns. Specifically, Dataset-1 pertains to experiments conducted on clayey soils, whereas Dataset-2 involves tests performed on peaty ground. It is pertinent to note that the principal objective within both original publications was the determination of the q_u of the treated foundation systems. Illustrative examples of the observed failure mechanisms for floating DCM columns, as documented in these studies, are depicted in Figs. 1(a) and (e). As the comprehensive details concerning sample preparation procedures and the analysis of failure modes are thoroughly discussed in earlier published papers (i.e [46, 47]).,, the scope of the present study is confined to the development and evaluation of predictive ML models.

To construct the predictive models, input parameters were selected based on the common variables available in the original experimental datasets from our previous publications. The chosen inputs include the column's length-to-diameter ratio (L/D), the area improvement ratio (A.I., expressed as a percentage), the undrained shear strength of the untreated soil (C_{us}, in kPa), and the ultimate bearing capacity of the improved soil (q_u, in kPa). The target variable is the undrained shear strength of the DCM column core material (C_{uc}, in kPa), which is explicitly chosen to support design applications.

This selection aligns with practical geotechnical engineering workflows for projects such as pavement foundations over soft ground, where engineers typically have prior knowledge of site-specific properties like the untreated soil's shear strength (C_{us}). In this study, q_u is used as an input parameter, reflecting common practice where designs are based on the required final bearing capacity. This value is determined according to project-specific pavement design codes and expected applied loads, which can differ across projects, thus enabling preliminary modelling and iterative design without the need for full-scale field testing. By incorporating logical design parameters for column geometry (L/D) and layout (A.I.) based on project requirements and engineering experience, the models are designed to estimate the necessary C_{uc} to achieve the desired overall performance of the improved ground, which is inherently tied to q_u.

2.1 Dataset Expansion Via SMOTE-like Interpolation

To address the limitation caused by the small initial dataset size (26 data points), which can lead to underfitting and poor generalisation in ML models, a data augmentation technique inspired by SMOTE-like interpolation was employed [48]. The fundamental concept is drawn from the Synthetic Minority Oversampling Technique (SMOTE), originally developed to address class imbalance in classification tasks. However, in this work, it is adapted for augmenting a regression dataset [48]. The core idea is to generate new, synthetic data points that are plausible and consistent with the characteristics of the existing data, rather than simply duplicating samples or adding random noise.

The methodology functions within the multi-dimensional feature space defined by the input variables. For each data

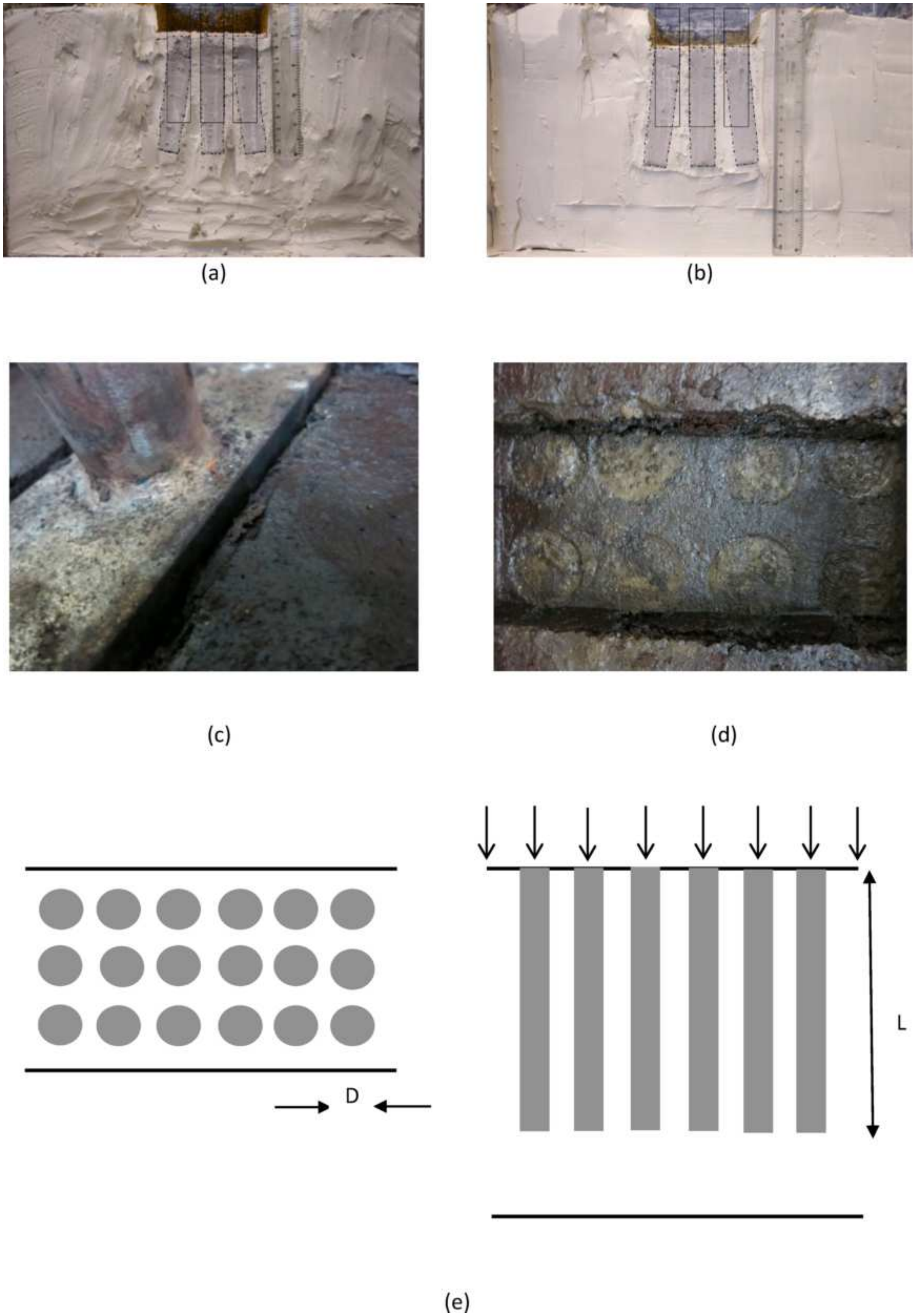


Fig. 1 **a** and **b** Dataset-1; **c** and **d** Dataset-2; and **e** layout of the DCM columns

point, one or more of its *'nearest neighbors'* (determined by Euclidean distance in the normalised feature space) are identified from the existing dataset. A new synthetic data point is then generated by interpolating along the line segment connecting the original data point and a randomly selected neighbour. This method calculates the difference vector between a point and its neighbor, scales it by a random value between 0 and 1, and adds the outcome to the original point's feature vector. By doing so, it generates new samples located between existing points, enhancing the data distribution density and producing a larger, more reliable dataset for training ML models [49].

After applying the SMOTE-inspired interpolation method, a sensitivity analysis was conducted to identify the optimal size of the augmented dataset. To achieve this, several ML models were trained and assessed using datasets of progressively increasing sizes, incorporating both the original and synthetically generated data points. The results of this sensitivity analysis indicated that a total dataset size of 250 samples was optimal. It was observed that when the dataset was expanded beyond this number, the improvements noted in key performance indices of the models were not statistically significant, suggesting diminishing returns with further data increase. Therefore, a final dataset size of 250 samples was adopted for subsequent model development and evaluation. A comparison of important statistical parameters between the original and augmented datasets is presented in Figs. 2(a-e).

(a) L/D.; (b) A.I; (%); (c) C_{us} (%); (d) q_u (kPa); and (e) C_{uc}.

L: Length of the column; D: Diameter of the column; A.I.: Area improvement ratio; C_{us}: Undrained shear strength of the soil; q_u: Ultimate bearing capacity; and C_{uc}: Undrained shear strength of the column.

2.2 Implementation and Tuning of Regression Models Via Pycaret

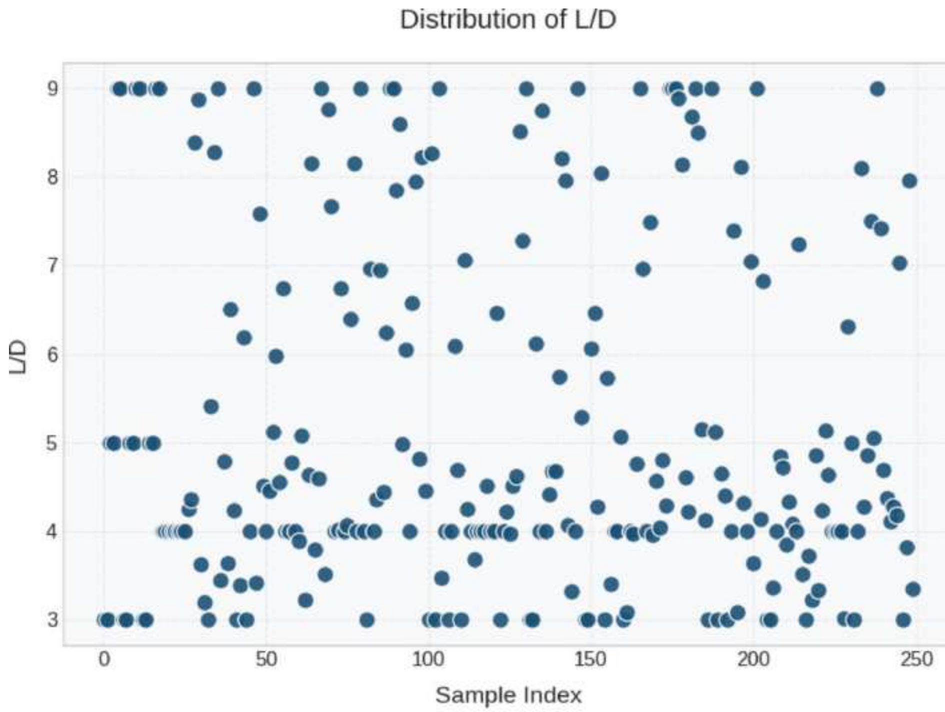
Once the dataset was prepared and augmented, a structured ML workflow was implemented using the PyCaret library. PyCaret, an open-source and low-code Python library, streamlines essential tasks such as data preprocessing, model selection, hyperparameter optimisation, and performance assessment. Its user-friendly interface facilitates rapid experimentation and comparison of multiple ML algorithms, making it well-suited for applied engineering problems [50]. The dataset, comprising 250 samples with L/D, A.I (%), C_{us} (kPa), and q_u (kPa) were used as input features, and C_{uc} (kPa) was used as the target variable. These features were divided into two distinct subsets: a training set and a test set. 70% of the dataset was allocated to the training set, which was used to train and optimise the ML models by capturing the relationships between the input features and the target variable. The remaining 30% served as the test set, reserved solely for assessing the models' predictive performance on unseen data. This separation ensures an unbiased assessment of how well the trained models generalise beyond the data they were exposed to during training, which is crucial for validating their practical applicability.

Subsequently, a comprehensive suite of nineteen distinct regression algorithms, facilitated by the Pycaret library, was trained using the designated training data. The initial performance of these diverse models was compared based on standard regression evaluation metrics, primarily focusing on the coefficient of determination (R^2) assessed through cross-validation within the training set. Based on this comparative analysis, the most promising candidate models were selected for further optimisation. Hyperparameter tuning was then performed on these selected models, utilising automated search techniques integrated within Pycaret to identify the optimal parameter configurations that maximised the chosen performance metric (e.g., R^2) during cross-validation. Finally, the single best-performing, fully tuned model was identified based on its cross-validated training performance and subsequently evaluated on the held-out test set to provide an unbiased assessment of its generalisation capability for predicting the target column shear strength (C_{uc}). The developed code is presented below:

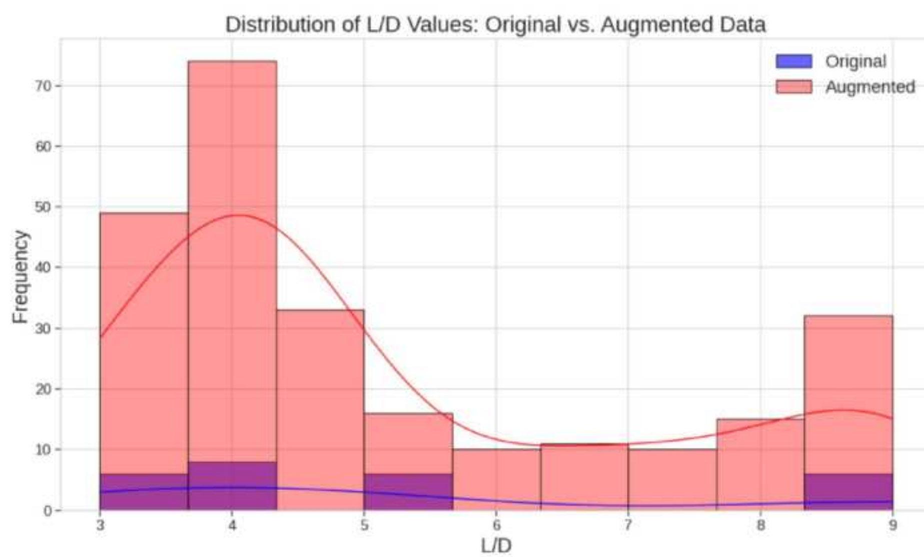
```
from pycaret.regression import *
import pandas as pd
data = pd.read_csv('data.csv')
exp = setup(data = data, target =' Cuc(kpa)', train_size = 0.7, fold = 10,
numeric_features = ['qu', 'A.I', 'L/D', 'Cus']
, preprocess = True, fold_strategy = 'kfold', session_id = 123)
gbr = create_model('gbr')
tuned_gbr = tune_model(gbr, optimize = 'R2')
feature_importance = get_feature_importance(tuned_gbr)
final_model = finalize_model(tuned_gbr)
save_model(final_model, 'gbr_model_final')
```

Algorithm

Fig. 2 Comparison of essential statistical parameters between the original and the augmented datasets. **a** −1, **a**−2, **b**−1, **b**−2, **c**−1, **c**−2, **d**−1, **d**−2, **e**−1, **e**−2

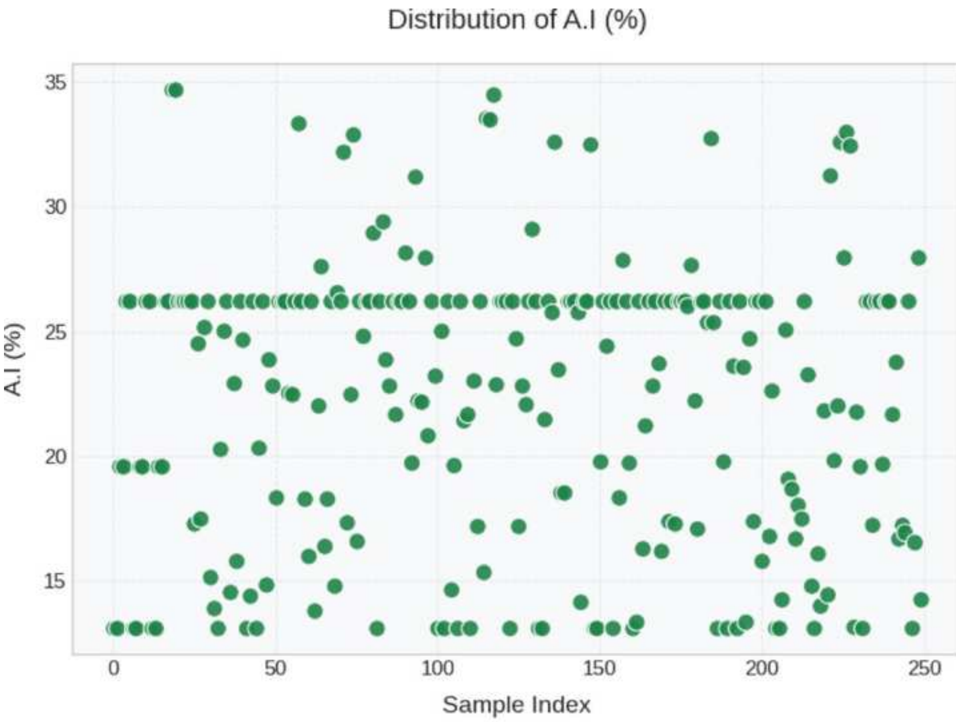


(a)-1

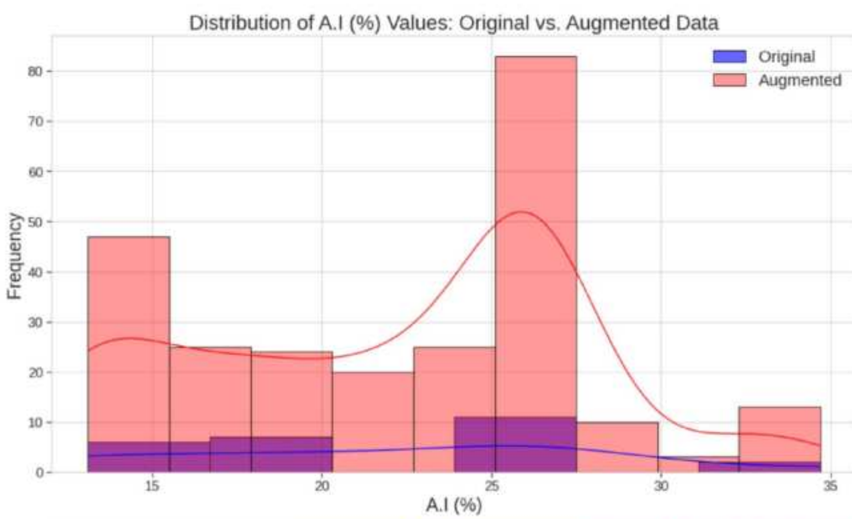


Metric	Original	Augmented
n	26	250
Mean	5.154	5.200
Median	4.000	4.360
Std Dev	2.257	1.969
Min	3.000	3.000
Max	9.000	9.000

(a)-2



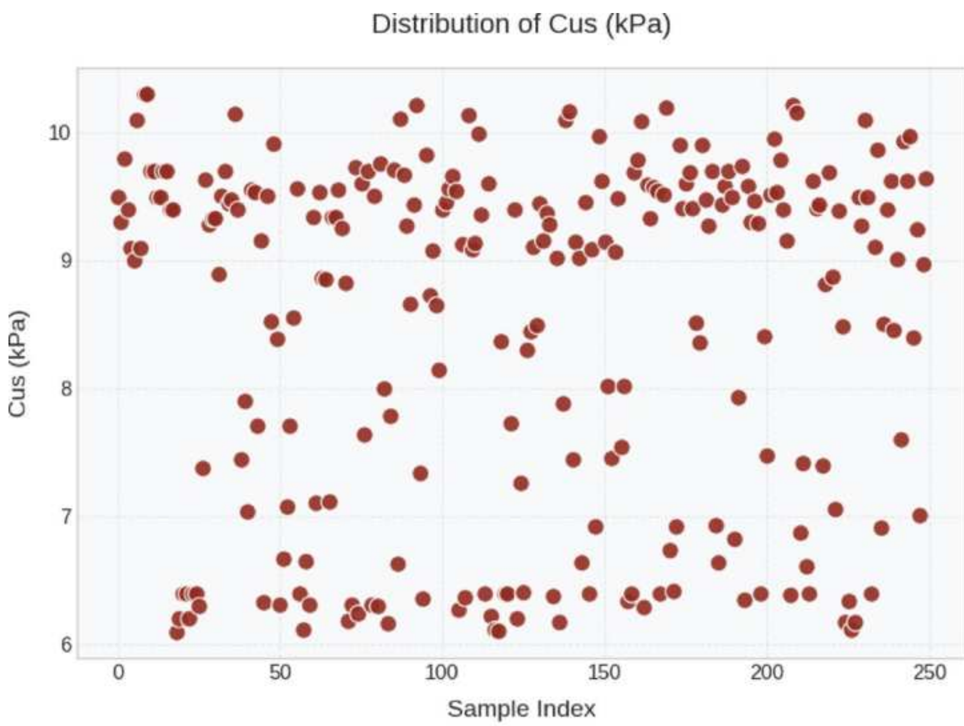
(b)-1



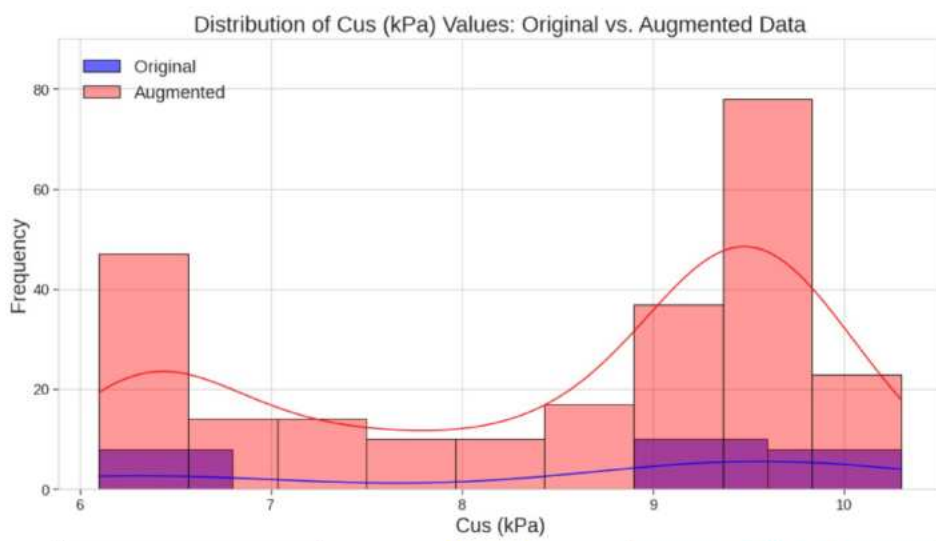
Metric	Original	Augmented
n	26	250
Mean	21.965	22.132
Median	22.900	23.390
Std Dev	6.476	5.720
Min	13.100	13.100
Max	34.700	34.700

(b)-2

Fig. 2 (continued)



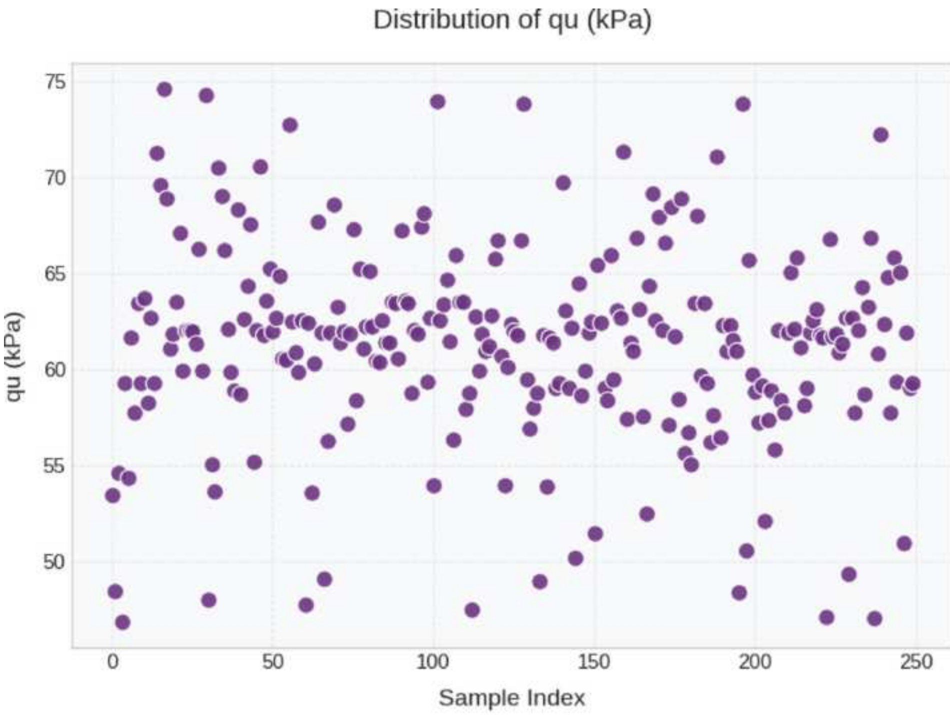
(c)-1



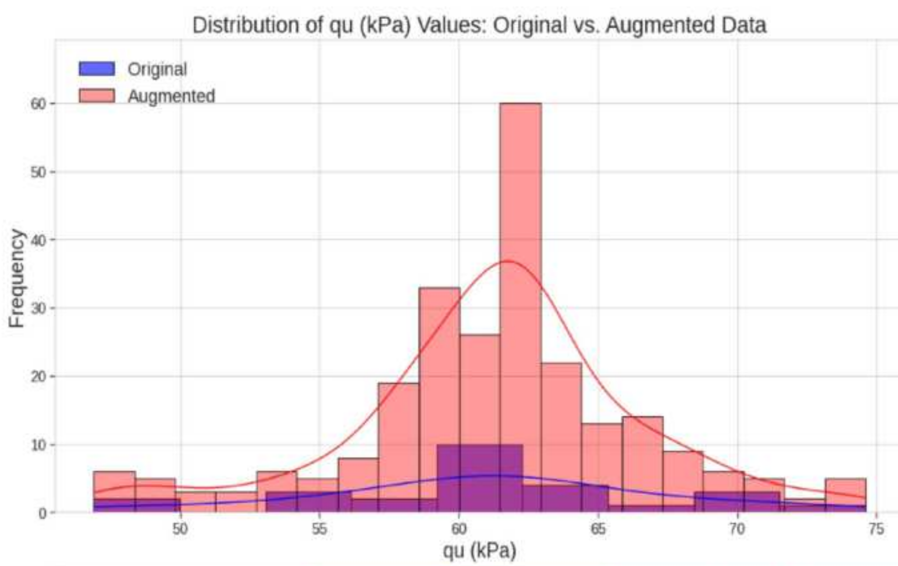
Metric	Original	Augmented
n	26	250
Mean	8.573	8.471
Median	9.400	9.121
Std Dev	1.577	1.362
Min	6.100	6.100
Max	10.300	10.300

(c)-2

Fig. 2 (continued)



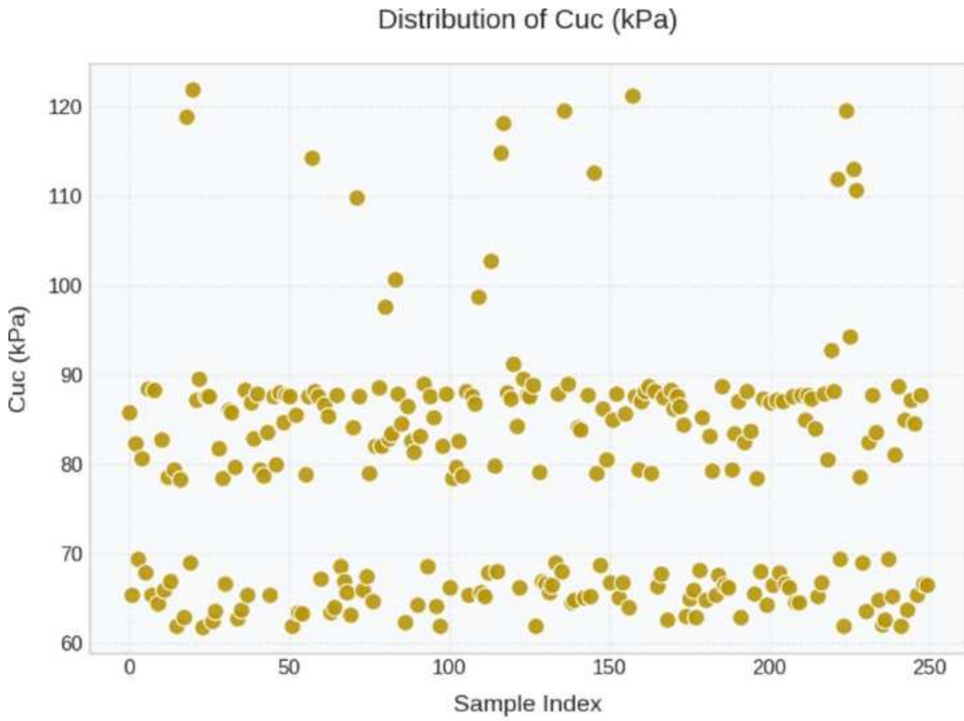
(d)-1



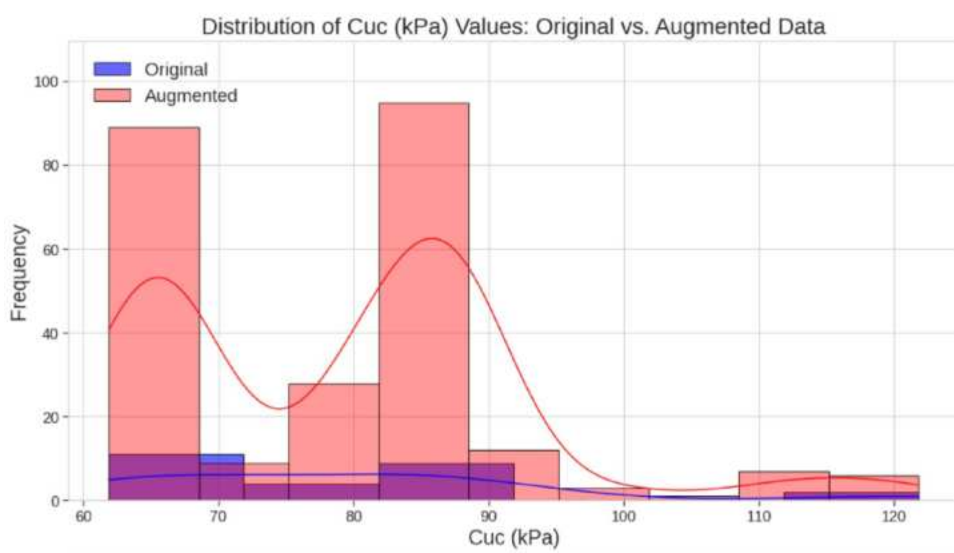
Metric	Original	Augmented
n	26	250
Mean	61.067	61.324
Median	61.775	61.839
Std Dev	6.374	5.206
Min	46.900	46.900
Max	74.600	74.600

(d)-2

Fig. 2 (continued)



(e)-1



Metric	Original	Augmented
n	26	250
Mean	79.203	79.249
Median	79.000	81.590
Std Dev	15.538	13.389
Min	61.880	61.880
Max	121.840	121.840

(e)-2

Fig. 2 (continued)

3 Results and Discussion

3.1 Machine Learning Model Performance Comparison

Following the implementation process described in the previous section, nineteen distinct ML regression models were trained and evaluated using the prepared dataset within the Pycaret framework. The performance of these models was compared based on standard regression metrics, and the results for the top ten performing models are summarised graphically.

Figure 3 presents a comparison of the coefficient of determination (R^2) values achieved by the top ten models on both the training and unseen testing datasets. As observed, the R^2 values obtained during training were consistently higher than those achieved during testing, a typical outcome in model development. The Gradient Boosting Regressor (GBR) model demonstrated the best predictive performance on the test set, achieving an R^2 value of 0.9310, indicating a strong alignment between its predictions and the actual target values. This performance was notably superior to that of the following best models, the AdaBoost Regressor (Ada) and Random Forest Regressor (RF), which achieved test R^2 values of 0.7640 and 0.7390, respectively. A noticeable decline in test performance was observed for subsequent models, including Extra Trees (ET, R^2 = 0.5950), XGBoost (R^2 = 0.5840), and Decision Tree (DT, R^2 = 0.5660). While models like gbr (Train R^2 = 0.9800), RF (Train R^2 = 0.8938), and ET (Train R^2 = 0.7193) showed high fitting capabilities on the training data, the gap between their training and testing R^2 scores suggests varying degrees of generalisation performance, with gbr showing the least drop-off among the very top performers.

Further insight into the models' fitting accuracy on the training data is provided by the Root Mean Squared Error (RMSE), presented in Fig. 4(a). Lower RMSE values signify less error between the predicted and actual values within the training set. The GBR model exhibited the lowest training RMSE (0.928 kPa), aligning with its top R^2 performance. The AdaBoost (RMSE = 0.756 kPa), Random Forest (RMSE = 0.732 kPa), and Extra Trees (RMSE = 0.589 kPa) models also displayed relatively low training errors. In contrast, models such as Huber Regressor (RMSE = 0.555 kPa), Linear Regression (RMSE = 0.549 kPa), Least Angle Regression (RMSE = 0.545 kPa), and Bayesian Ridge (RMSE = 0.482 kPa) showed comparatively higher training errors, consistent with their lower R^2 values observed in Fig. 3.

Complementing these RMSE results, the Mean Absolute Error (MAE) values presented in Fig. 4(b) further illustrate the models' training accuracy. GBR achieved the lowest MAE (2.125 kPa), followed by AdaBoost (2.986 kPa), Random Forest (3.931 kPa), and Extra Trees (4.965 kPa), indicating better predictive precision. Models such as Decision Tree (11.756 kPa), Huber Regressor (15.323 kPa), Linear Regression (21.369 kPa), Least Angle Regression (26.545 kPa), and Bayesian Ridge (33.998 kPa) exhibited substantially higher MAE values, in agreement with their elevated RMSE and lower R^2 metrics.

Considering both the high R^2 value on the test set (indicating good generalisation) and the low RMSE on the training set (indicating good fit), the gbr model emerged as the most effective single model identified through the initial Pycaret comparison for predicting the target variable based on the provided input features. The Ada and RF models also demonstrated reasonably strong performance, particularly in terms of test R^2.

Based on these comparative findings, the GBR stands out as the most suitable model for this geotechnical application due to its exceptional predictive performance. This ML model employs an ensemble approach, constructing a sequence of

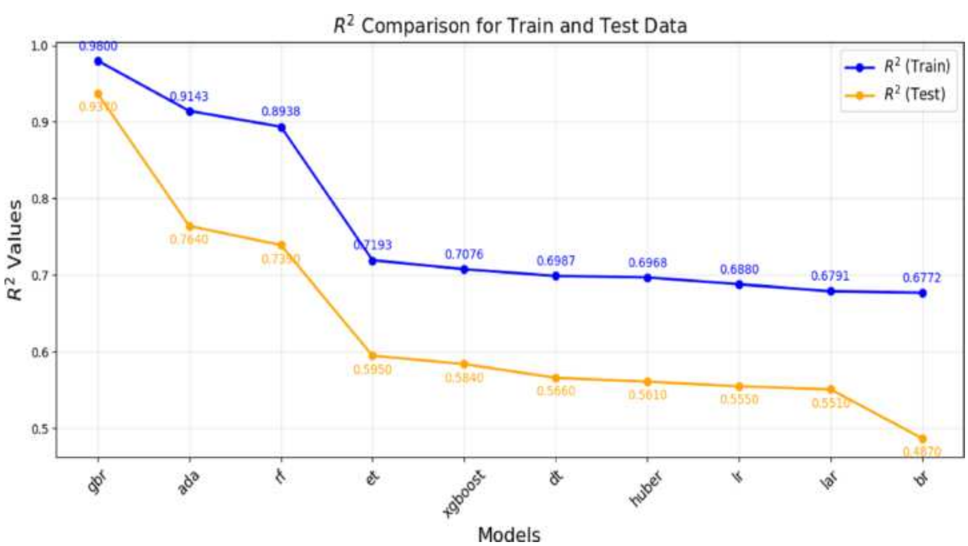
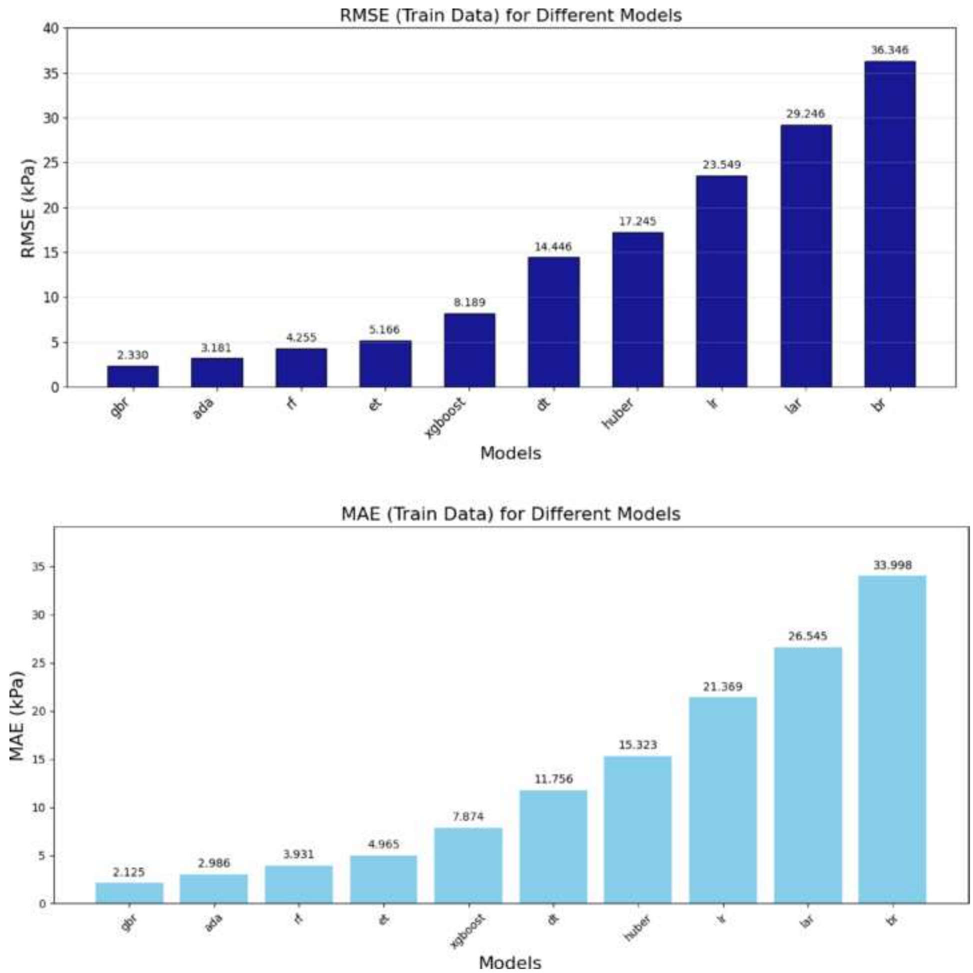


Fig. 3 Coefficient of determination (R^2) values for the top ten performing models

Fig. 4 **a** Root Mean Squared Error (RMSE) of the ML models; and **b** Mean Absolute Error (MAE) of the ML models



weak prediction models, typically decision trees, where each successive model aims to address the errors of the previous ones. This iterative error-correction process enables the algorithm to effectively capture complex nonlinear relationships between input features and target variables, which is especially beneficial in geotechnical applications where material behaviour often demonstrates significant nonlinearity [50].

The model's exceptional performance can be attributed to several inherent advantages: its robustness against overfitting through regularisation parameters, ability to handle heterogeneous data without extensive preprocessing, natural capacity to model feature interactions without explicit specification, and built-in feature importance assessment capabilities. These characteristics make gbr particularly well-suited for geotechnical problems where the underlying physical mechanisms involve multiple interacting variables with varying degrees of influence [51–53]. Furthermore, the algorithm's adaptability through hyperparameter tuning allows it to balance model complexity against generalisation performance, as evidenced by the minimal gap between its training and testing R^2 values compared to other high-performing models in this study [54].

3.2 Tuning and Final Performance of the Gbr Model

The initial comparative analysis presented in the results section identified the gbr as the most effective model among those evaluated, demonstrating superior predictive capability for estimating the column strength (C_{uc}) with the highest R^2 value (0.9310) on the unseen test data. Consequently, the gbr model was selected as the primary candidate for further enhancement through hyperparameter optimisation. This refinement step is critical in ML model development, as careful tuning of hyperparameters significantly influences a model's final predictive accuracy and its ability to generalise effectively to new, unseen data, while mitigating risks of overfitting or underfitting [55]. Automated hyperparameter tuning procedures, such as those provided by the Pycaret library used in this study, offer efficiency compared to manual optimisation techniques [50].

The gbr algorithm itself is an ensemble method rooted in boosting principles. It constructs a strong predictive model by sequentially adding weak learner models, typically decision trees. Each new tree added to the ensemble is specifically trained to correct the residual errors made by the preceding combination of trees. This sequential process allows the model to incrementally improve its predictions by focusing on the instances that were previously difficult to predict accurately. gbr incorporates mechanisms to handle both numerical and categorical features and often includes methods for managing missing data. A key parameter is the learning rate, which scales the contribution of each individual tree; smaller learning rates generally require more trees (estimators) but can lead to better generalisation by preventing overly rapid convergence [50].

Utilising Pycaret's automated tuning functions, an optimised set of hyperparameters was determined for the GBR model to maximise its performance on the Cuc estimation task. Notably, the optimised model employed a learning rate of 0.05, indicating a relatively conservative learning step size. The complexity of individual trees was controlled by setting max_depth to 6. The ensemble consisted of 310 sequential trees (n_estimators). Regularisation and tree construction were further guided by parameters such as min_samples_split (4), min_samples_leaf (4), max_features ('sqrt' - considering the square root of the total features at each split), and subsample (0.3 - using 30% of the data for fitting each tree), which help prevent overfitting. The random_state was set to 2451 to ensure reproducibility of the tuning results.

The effectiveness of the final, tuned gbr model is demonstrated in Fig. 5. This figure presents a scatter plot comparing the experimentally determined C_{uc} values (horizontal axis) against the C_{uc} values estimated by the optimised gbr model across the entire dataset. A strong positive linear relationship is clearly visible, with the data points tightly clustered around the ideal prediction line. The high fidelity of the model is quantitatively confirmed by the performance metrics displayed on the plot, where an R^2 of 0.9652 was achieved, indicating that the tuned GBR model explains over 96.5% of the variability observed in the experimental C_{uc} data. Furthermore, the MSE was found to be 6.2104 (kPa), indicating a very low average squared difference between the experimental measurements and the model's predictions. These results underscore the success of the hyperparameter tuning process and validate the tuned gbr model as a highly accurate tool for estimating deep cement column core strength based on the input parameters used in this study.

3.3 Sensitivity Analysis

A sensitivity analysis was carried out using PyCaret's built-in functionality to assess the relative impact of each input parameter on the undrained shear strength of DCM columns. This analysis systematically varies each input parameter while keeping others constant, measuring the resulting changes in the predicted output. Known as feature importance evaluation, this method quantifies the contribution of each parameter to the model's predictions. By permuting the values of each feature and observing the corresponding decline in model performance, the approach identifies the features with the most significant influence on predictive accuracy.

The four top-performing models of gbr, ada, rf, and et were utilised for this sensitivity analysis to ensure robustness of the findings. By incorporating multiple models in the sensitivity analysis, the consistency of parameter importance rankings could be assessed across different algorithmic approaches, providing greater confidence in the results. Each model was evaluated to determine the relative importance of the four input parameters (qu, C_{us}, A.I, and L/D) in predicting the C_{uc} of the DCM columns. As shown in Fig. 6, all four models consistently identified q_u as the most influential parameter, with relative importance scores ranging

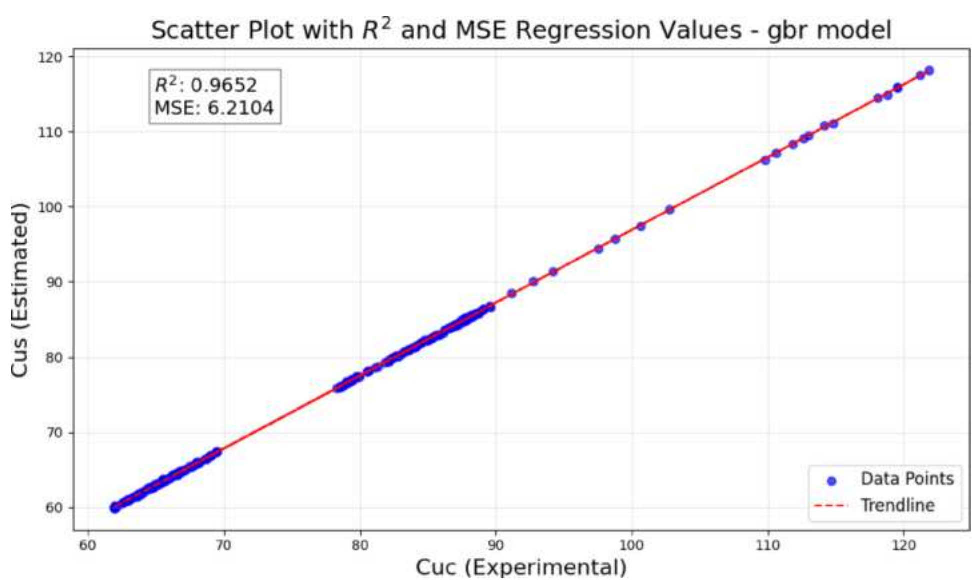


Fig. 5 Performance indices of the tuned_gbr model

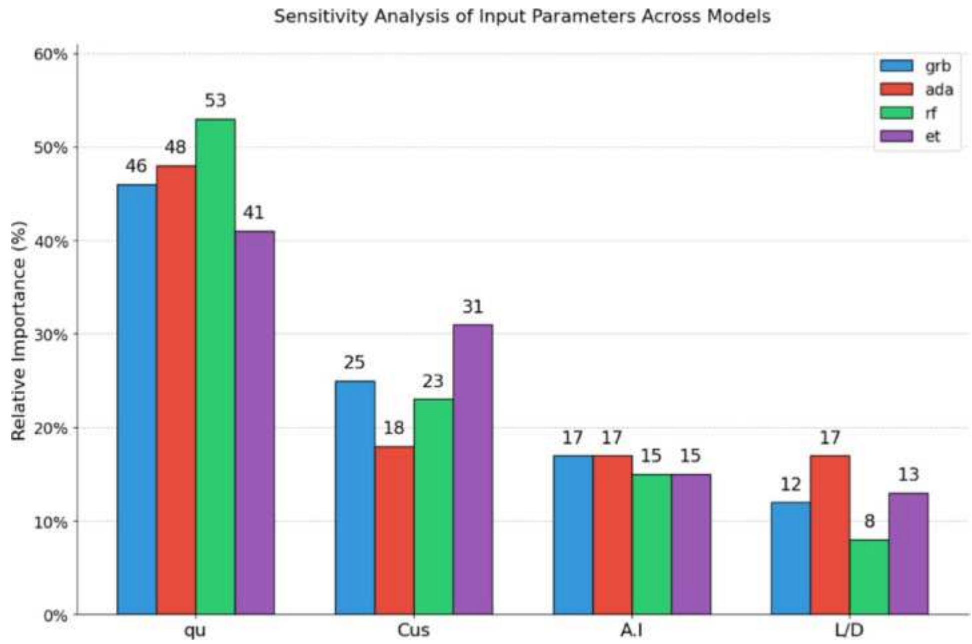


Fig. 6 The sensitivity analysis results of the ML models

from 41% (et model) to 53% (rf model). This finding aligns with fundamental geotechnical principles, as q_u serves as the primary performance criterion directly influencing the strength requirements of the improved ground system. The prominence of q_u in the sensitivity analysis highlights that the design strength of DCM columns is predominantly governed by bearing capacity demands, emphasising the load-driven nature of DCM design.

The sensitivity analysis in this study indicated that the undrained shear strength of the surrounding soil is a critical factor influencing the required shear strength of DCM columns, with importance values ranging from 18% to 31%. In practical terms, enhancing C_{us} before DCM installation can reduce the structural demand on the columns and improve overall ground performance. In field conditions, C_{us} can be improved through several ground improvement techniques, including preloading with or without vertical drains to accelerate consolidation, surcharging, in-situ cement or lime stabilisation, and controlled compaction methods where applicable. The choice of technique depends on soil type, groundwater conditions, project timeline, and environmental constraints. By strategically improving the native soil's strength before column installation, engineers can optimise design parameters, potentially reduce the number or size of columns needed, and achieve cost and material savings while maintaining or improving pavement foundation performance.

Interestingly, the area improvement ratio demonstrated moderate importance (15–17%) across all models, while the length-to-diameter ratio (L/D) showed greater variability in importance (8–17%) between different models. The consistently higher importance of C_{us} compared to A.I suggests that the intrinsic strength properties of the soil matrix play a more substantial role in determining the required DCM column strength than the geometric arrangement or relative area of the columns.

3.4 Model Deployment for Practical Engineering Use

To facilitate the direct application of the findings by practitioners, a deployment strategy was developed for the optimised ML model. This involved packaging the final tuned_gbr model, inclusive of any necessary data preprocessing steps learned during training (such as feature scaling or transformations handled internally by Pycaret), into a reusable pipeline. The objective was to create a user-friendly mechanism enabling geotechnical engineers to rapidly and accurately estimate the required column core strength (C_{uc}) for new design scenarios without needing to rebuild or retrain the model.

The machine learning pipeline created in this study using the PyCaret framework was designed for direct integration into professional geotechnical workflows. In its current form, the tool can be implemented in Python by importing the trained model, inputting site-specific geotechnical parameters, and executing a simple prediction command to obtain the required undrained shear strength (C_{uc}) of DCM columns. This automated process abstracts away the complexities of model execution and data handling, allowing the focus to remain on the engineering interpretation and application of the prediction for tasks such as mix design optimisation. The practical deployment of this model can be achieved using the functionalities available within the

Pycaret library. The entire trained pipeline, which includes both the data transformation steps and the tuned_gbr model itself, can be saved as a single object. This saved pipeline can then be loaded into any Python environment where Pycaret is installed to make predictions on new datasets. The basic sequence involves saving the finalised experiment/pipeline, loading it when needed, and then using the predict_model function, as shown in the following code.s.

loaded_experiment_pipeline = load_experiment('C_{uc}_Prediction_Experiment', data = new_data_df) (1).

3.5 Limitations of the Study and Future Recommendations

The present study, while demonstrating the effectiveness of ML methods in predicting DCM column strength, has several limitations. The main restriction is the dependence on a relatively small experimental dataset, which, despite augmentation techniques increasing the sample size from 26 to 250, may not fully represent the complex field conditions faced in real-world applications. As a result, the models' predictive ability is limited by the parameter ranges examined in the experimental programme, restricting reliable prediction beyond those limits. Furthermore, laboratory testing primarily focused on specific soil types under simplified axial loading conditions, which may not accurately reflect the diverse soil properties and complex loading scenarios—such as cyclic, dynamic, and eccentric loading—that occur in the field. The current modelling approach also does not explicitly include construction variables such as mixing efficiency and installation techniques, or the time-dependent behaviour of DCM columns, both of which can significantly influence actual field performance. Future research should aim to expand the experimental database by incorporating field data from real DCM projects across varied soil conditions and loading scenarios. This will improve the robustness and real-world applicability of predictive models by accounting for variability and complexities. Additionally, it is recommended to expand the input feature set to include more geotechnical and construction-related parameters, such as cement dosage, curing time, and site-specific soil properties. Integrating data from field logs, sensor measurements, and real-time monitoring will enable more comprehensive modelling of DCM column behaviour and enhance predictive accuracy.

While the application of SMOTE-like interpolation and other augmentation techniques addresses the limitation of small experimental datasets, the use of synthetic data may influence the model's generalisation capability. Since the synthetic samples are generated based on the statistical relationships present in the original dataset, they do not introduce entirely new physical scenarios beyond the observed range, which may lead to overfitting if the generated patterns do not fully represent the variability of in-situ conditions. To mitigate this risk, the augmented dataset in this study was constructed with tight geotechnical constraints to ensure physical plausibility, and model evaluation was performed using stratified cross-validation to minimise bias. Nonetheless, the model's predictive accuracy should be interpreted with the understanding that field conditions deviating significantly from the original experimental domain may require additional data collection for optimal performance.

Although this study briefly introduced the concepts of floating DCM columns, the depth improvement ratio (D.I.)—defined as the ratio between the DCM column length and the thickness of the soft soil layer [56] was not explicitly included as an input parameter in the ML modelling framework. This ratio is recognised in geotechnical research and practice as a significant factor influencing load transfer mechanisms, consolidation behaviour, and the overall performance of floating columns, particularly in thick, soft clay deposits. The omission in this study is primarily related to the limited scope and resolution of the available dataset, which lacked consistent and sufficient D.I.-related measurements for robust model training. Future work, particularly with access to larger or field-scale datasets, should incorporate D.I. as a predictive parameter to enable more accurate modelling of the transition between floating and end-bearing column behaviour. This enhancement could improve the model's capacity to adapt to a broader range of soil profiles and ground improvement configurations.

Additionally, implementing a systematic field validation program that compares model predictions with the actual performance of DCM installations would offer vital feedback for ongoing model improvement and enhance practitioner confidence. Lastly, expanding the models to optimise multiple design parameters at once, balancing performance goals with economic factors, would transform these tools into comprehensive decision-support systems, enabling more efficient and reliable geotechnical design and construction.

4 Conclusions

This study aimed to develop a data-driven method for estimating the required undrained shear strength of DCM columns in pavement foundation systems. By combining two experimental datasets and employing machine learning techniques to address the limitations of traditional analytical methods, we have shown the potential of machine learning-based design approaches in geotechnical engineering. The research addressed the challenge of limited experimental data by employing strategic data augmentation while preserving the essential physical relationships necessary for geotechnical validity. A comprehensive evaluation of regression algorithms and sensitivity analysis led to several important conclusions:

- The study highlights the importance of combining data augmentation methods with ML algorithms to address data scarcity issues in geotechnical research, creating a framework that can be applied to other ground improvement projects.
- The Gradient Boosting Regression (gbr) algorithm proved to be the best modelling technique among the four top-performing models (gbr, ada, rf, and et), achieving excellent predictive accuracy with an R^2 of 0.965 and MSE of 6.21 kPa, confirming its suitability for DCM column strength estimation.
- Sensitivity analysis consistently identified the q_u as the most influential parameter (41–53%) across all models, followed by the undrained shear strength of the surrounding soil (C_{us}) at 18–31%. Meanwhile, geometric factors such as area improvement ratio and length-to-diameter ratio showed comparatively lower importance.
- The findings challenge traditional design methods by suggesting that enhancing the soil's strength before DCM installation could be more effective than simply enlarging column sizes or increasing the area improvement ratio, potentially resulting in more efficient and cost-effective designs.
- The successful creation of a deployable model pipeline enables practising engineers to implement it directly, effectively bridging the gap between advanced computational techniques and practical geotechnical design applications.
- Future validation of this model using independent laboratory or field-scale datasets is recommended to confirm its robustness and applicability across various geotechnical conditions, including real-world soil variability.

Collectively, these conclusions advance the state-of-practice for designing DCM-reinforced pavement foundations, introducing a robust data-driven paradigm that stands as a viable alternative to established analytical methods while preserving direct relevance to real-world geotechnical engineering challenges.

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Data Availability Data will be made available upon reasonable request.

Declarations

Conflict of Interest The authors declare that there is no conflict of interest in presenting this manuscript.

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Consent for Publication This study does not include identifiable information about individuals or entities.

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