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Data Driven Approach for Estimating Factor of Safety against Overturning in Geotextile Reinforced Walls using Machine Learning Models

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Abstract

In the preliminary design of geotextile-reinforced walls, the integration of data-driven machine learning models has ushered in a new era of predictive accuracy and efficiency. This paper presents the development and evaluation of three distinct machine learning models: Artificial Neural Network (ANN), Support Vector Machines (SVMs), and Gradient Boosting (GB), as tools to enhance the design process. The methodology entails the selection of input data, coupled with the application of analytical methods to ascertain the factor of safety against overturning for geotextile-reinforced walls. The study harnesses eight input parameters, each with a range of values, and employs analytical techniques to derive the crucial factor of safety. Subsequently, these input-output pairs are fed into the machine learning models, facilitating the training and testing phases. The results of model performance assessment reveal that both ANN and GB models outshine SVMs in predicting the factor of safety. These findings underscore the potential of machine learning in advancing the accuracy and efficacy of geotechnical design, offering a promising avenue for future engineering applications.

Keywords

Factor of safety, Overturning, Geotextile, Machine Learning

1. Introduction

Soils exhibit inherent weaknesses in tension and comparatively higher strength in compression. To address this discrepancy and enhance soil stability, mechanical reinforcement is often employed, with various materials such as metal strips, non-biodegradable fabrics, and geogrids being commonly utilized. Among these options, geotextiles have gained significant traction on a global scale. Geotextiles offer multifaceted functionality, including drainage, filtration, separation, and reinforcement, making them valuable assets in foundation engineering and the construction of retaining wall structures. In the context of retaining wall structures, geotextiles are strategically positioned within the layers of granular backfill soil. This positioning imparts tensile strength to the structure, bolstering its overall stability and facilitating the construction of taller walls. Geotextiles effectively serve as a structural sandwich between the granular backfill soil layers. Designing geotextile-reinforced walls necessitates a thorough evaluation, focusing on both internal and external stability criteria.[1] Traditionally, verifying this stability involves complex and time-consuming analytical methods, especially when conducting parametric studies. In our research, we aim to revolutionize this approach by leveraging a data-driven methodology to determine the Factor of Safety (FOS) against overturning. The data-driven approach has garnered attention from researchers [2, 3, 4, 5], worldwide for its ability to predict geotechnical reliability and establish correlations among linear and nonlinear parameters efficiently. While linear and nonlinear analyses typically require extensive time and effort, artificial intelligence and machine learning models provide a streamlined solution.[5] These models allow for the creation of correlation models, enabling rapid parametric variations. In our study, we employ three machine learning algorithms: Artificial Neural Network, Gradient Boosting, and Support Vector Machines, to predict the FOS against overturning for geotextile-reinforced walls. The subsequent sections of this paper will delve into the methodology, encompassing data collection and analysis, model development, and validation. Through these efforts, we aim to shed light on the practical advantages and implications of adopting a data-driven approach in assessing the FOS against overturning for geotextile walls.

1.1 Geotextile Reinforced Walls

Geotextile reinforcement, typically composed of materials derived from petroleum products, serves multifunctional roles, including drainage, filtration, separation, and reinforcement. This versatility makes it a key component in the construction of reinforced soil walls and foundation engineering projects. The design of such structures necessitates careful consideration of both internal and external stability factors.

1. Internal Stability The process encompasses the calculation of spacing and length for each geotextile layer, focusing on achieving a factor of safety for pullout ranging from 1.3 to 1.5. Additionally, it entails the design of geotextile layers to ensure a factor of safety against tie failure, accounting for reductions in ultimate tensile strength due to reduction factors [1].

2. External Stability The study primarily revolves around the evaluation of the factor of safety against overturning,

sliding, and bearing capacity. Specifically, our focus lies on the factor of safety against overturning, which is determined as follows:

$$\mathrm{FS}_{\text{overturning}} = W \cdot \frac{x}{P_a \cdot \frac{H}{3}} \tag{1}$$

$$W = H \cdot L \cdot \gamma \tag{2}$$

$$x = \frac{L}{2} \tag{3}$$

$$P_a = \frac{1}{2} \cdot \gamma \cdot (H)^2 \cdot K_a \tag{4}$$

where γ is Unit weight of backfill, K_a is Rankine active pressure coefficient, L is length of each layer of geotextile , here length of each layer of geotextile is calculated considering maximum value and same in all layers.

1.2 Machine Learning Algorithms

1.2.1 Artifical Neural Network(ANN)

McCulloch and Pitts first introduced Artificial Neural Networks (ANN). Artificial Neural Network (ANN) is one of the most commonly used AI techniques in geotechnical Engineering, and offers to be a promising tool in modeling of complex engineering problems, where the relationship between the model variables is unknown 5, or physical visualization is difficult [6]. As described by [2], a parallel distributed processor called an ANN is able to store and process data from a set that was contributed outside of the network. ANN learns from training patterns and exemplary input-output relations provided to it [6]. The input, output, and hidden layers of an artificial neural network (ANN) are made up of a lot of simple, highly connected processing elements (PEs) called neurons [2]. Weighted connections allow these logically structured layers to speak with one another [2]. Each neuron is connected to every other neuron in the layer above it. The input layer shows the network a pattern. One or more hidden layers communicate with the input layer. The actual processing happens in the hidden layers, where a network of weighted connections establishes a connection between the inputs and outputs. A typical ANN structure can be visualized from Figure 1.

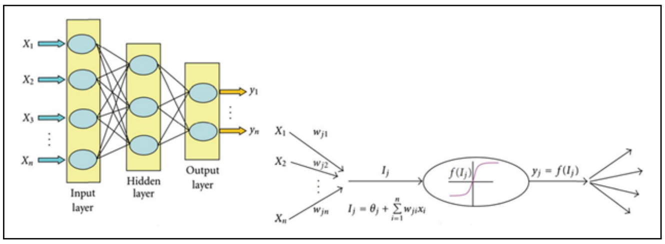

Figure 1: Typical working structure of ANN [2]

1.2.2 Support Vector Machines (SVMs)

A supervised machine learning model suitable for both classification and regression problems is represented by support vector machines (SVMs)[7]. SVMs are fundamentally based on the idea of finding an optimal hyperplane that can accurately separate different classes present within the training dataset[8]. Hyperplanes, which can manifest as lines in two dimensions, planes in three dimensions, or more complex constructs in higher-dimensional spaces, function as crucial decision boundaries[7]. SVMs seek to identify the optimal hyperplane that maximizes the separation, referred to as the margin, between this hyperplane and the closest data points belonging to each class [9]. Given their critical significance in setting the location and direction of the hyperplane, which enables reliable classification or regression, these crucial data points are known as support vectors [10]. SVMs possess the capability to manage nonlinearly separable data through a method known as the kernel trick [10]. The kernel trick involves a transformation of the original data into a higher-dimensional space, enabling the discovery of a linear hyperplane within that space [10]. Various kernel functions, including polynomial, radial basis function, and sigmoid kernels, can be employed to capture distinct forms of nonlinearity present in the data [11]. Support Vector Machines (SVMs) offer several advantages, including exceptional accuracy, resilience to outliers, and the capability to effectively manage high-dimensional datasets [9]. Nonetheless, SVMs come with certain limitations, including substantial computational demands, susceptibility to parameter choices, and a deficiency in interpretability [10].

1.2.3 Gradient Boosting

Gradient boosting serves as a crucial machine learning technique widely employed across various applications, encompassing regression and classification tasks[12]. Its central concept revolves around constructing a prediction model, notably an ensemble consisting of weak prediction models, often in the form of modest decision trees [13]. The fundamental concept that forms the basis of gradient boosting revolves around an iterative process aimed at continually refining prediction accuracy [5]. This process unfolds by gradually introducing new weak models, with each one assigned the responsibility of correcting the errors made by its predecessors. [13]. Vitally, the creation of these novel models relies on aligning them with the negative gradient of the loss function, which serves as a measure of the model's adherence to the data [12]. Gradient boosting showcases its versatility by supporting a wide range of loss functions, including binary or multiclass log loss, mean squared error, and Huber loss. Moreover, it offers extensive configurability through parameter tuning, allowing for fine-tuning adjustments to parameters such as the number of trees, learning rate, tree depth, and regularization term [5]. Despite being renowned for its exceptional predictive capabilities, adaptability, and scalability, gradient boosting does have its inherent limitations [5]. It may be vulnerable to overfitting, demands careful parameter tuning, and presents difficulties when it comes to interpretability [12].

2. Methodology

The method used in this study involves the generation of the factor of safety against overturning using the analytical method

Table 1: Input and Output Parameters

Parameters	Unit	Symbol	Range	Category
Wall Height	m	H	5, 6, 6.5, 7	Input
Unit weight of backfill	kN/m³	γ	15, 16, 16.5, 18	Input
Internal angle of friction of backfill soil	radians	ϕ	0.5934, 0.5236, 0.5585, 0.6283	Input
Ultimate Tensile Strength	kN/m³	T_{ult}	50, 52.5, 55, 60	Input
Reduction Factor for installation damage	-	RF_{id}	1.4, 1.5, 1.6, 1.7	Input
Reduction factor for creep	-	RF_{cr}	2.5, 2.75, 3, 3.5	Input
Reduction factor for chemical and biological degradation	-	RF_{cbd}	1.2, 1.25, 1.4, 1.5	Input
Ratio of friction angle	-	$\frac{\phi_f}{\phi}$	0.8, 0.86, 0.87, 0.92	Input
Factor of Safety for overturning	-	$FOSo$	3.0626-3.4218	Output

suggested by [1] and feeding the data into the machine learning model. The following represents the methodology process:

1. Database Preparation:

   Table 1 shows the input parameters chosen within the limit.

   The values for the factor of safety against pullout and tie failure were fixed, and the reduction factor to reduce ultimate tensile strength was taken within the limit suggested by [1]. For the calculation of the factor of safety against overturning, steps by [1] were taken. The variations of data in database preparation is shown in Table 1.

2. Model Preparation:

   (a) ANN:

   The methodology outlined in this research paper employs a machine learning approach to predict the "Factor of Safety for overturning" in a given context. The study begins by loading a dataset from a CSV file, which contains both input features and the target output. The input data is then preprocessed and normalized using standard scaling techniques to ensure that all features have similar scales, thus preventing any one feature from dominating the model's learning process. To assess the predictive capability of the model, the dataset is split into training and testing sets using a 80%-20% split ratio. The machine learning model chosen for this task is a neural network constructed using the TensorFlow and Keras libraries. The neural network architecture consists of an input layer with eight nodes (matching the number of input features), followed by two hidden layers with 64 and 32 neurons, respectively, both employing ReLU activation functions. The final output layer, designed for regression, contains a single node. For model training, the Adam optimizer is utilized with the mean squared error loss function, and the model is evaluated based on the mean absolute error metric. The training process involves 50 epochs with a batch size of 32. Once trained, the model is used to make predictions on the testing set, and the R-squared (R^2) metric is employed to assess the model's predictive accuracy. Finally, a scatter plot is generated, displaying the relationship between actual and predicted values, along with the (R^2) value to provide insights into the model's performance.

   (b) Gradient Boosting:

   Firstly, the dataset is loaded from a CSV file, splitting it into input features (X) and the target output (y), where the target variable represents the structural stability measure. Next, to enhance model performance and convergence, the input features are standardized using the Standard Scaler. While not always obligatory for Gradient Boosting, this preprocessing step ensures that all features share a consistent scale.

   The dataset is then divided into training and testing sets, allocating 80% for model training and reserving 20% for evaluation. This separation is crucial to assess how well the model generalizes to unseen data.

   The model is trained using the training dataset, refining its predictions iteratively to minimize errors and optimize its fit to the target variable. Once training is complete, the model is employed to make predictions on the testing dataset. This allows for the assessment of its performance on previously unseen data.

   Performance evaluation is conducted using two fundamental metrics: R-squared (R^2) gauges the model's ability to explain variance in the target variable, while Mean Absolute Error (MAE) quantifies the average magnitude of errors between predicted and actual values.

   To provide a visual representation of the model's performance, a scatter plot is generated, illustrating the relationship between actual and predicted values.

   (c) Support Vector Machines:

   In this methodology, we employ Support Vector Machines (SVM), specifically a Support Vector Regressor (SVR), with a polynomial kernel to predict the Factor of Safety for overturning in geotextile-reinforced walls. The process commences by loading the relevant dataset from a CSV file, which includes both input features and the target output variable representing structural stability.

   To ensure the model's performance and convergence, we apply feature standardization using the Standard Scaler. This step is particularly crucial when working with SVM models, as they are sensitive to variations in feature scales.

   Subsequently, the dataset is split into training and testing sets, with 80% allocated for model training and 20% reserved for evaluation. This division is essential to assess the model's ability to generalize its predictions to unseen data accurately.

We create an SVR model with a polynomial kernel, and hyperparameters such as the degree of the polynomial kernel can be adjusted to fine-tune the model's behavior. The SVR model is then trained using the training dataset, iteratively refining its predictions to minimize errors and optimize its fit to the target variable.

After training, the model is employed to make predictions on the testing dataset, enabling the assessment of its performance on data it hasn't encountered before. To evaluate the model's performance, we utilize two key metrics: R-squared (R^2) to measure its ability to explain variance in the target variable and Mean Absolute Error (MAE) to quantify the average magnitude of errors between predicted and actual values.

To provide a visual representation of the model's predictive capability, we generate a scatter plot that displays the relationship between actual and predicted values. Additionally, a trendline is added to the plot, showing the linear relationship between these values. This trendline helps in visualizing how well the model's predictions align with the actual data points.

3. Results

The individual performance plots for each machine-learning model are presented, revealing distinctive insights into their predictive capabilities. Artificial Neural Networks (ANN) and Gradient Boosting exhibit remarkable proficiency in forecasting the factor of safety against overturning for geotextile-reinforced walls. Conversely, Support Vector Machines (SVMs) lag significantly behind in their predictive power among the three machine learning models employed in this study. This discrepancy may be attributed to the hyperparameters governing the SVM algorithm, highlighting the importance of fine-tuning model settings for optimal performance.

In summation, the data-driven approach adopted in this study has yielded valuable insights into the factor of safety against overturning in geotextile-reinforced walls. By leveraging machine learning techniques, this research empowers engineers to explore parametric variations in the preliminary design of such structures. The superior performance of ANN and Gradient Boosting models underscores their potential to enhance the accuracy and efficiency of geotechnical design processes. These findings illuminate a promising avenue for future applications, emphasizing the importance of tailoring machine learning algorithms to the specific nuances of geotechnical engineering challenges.

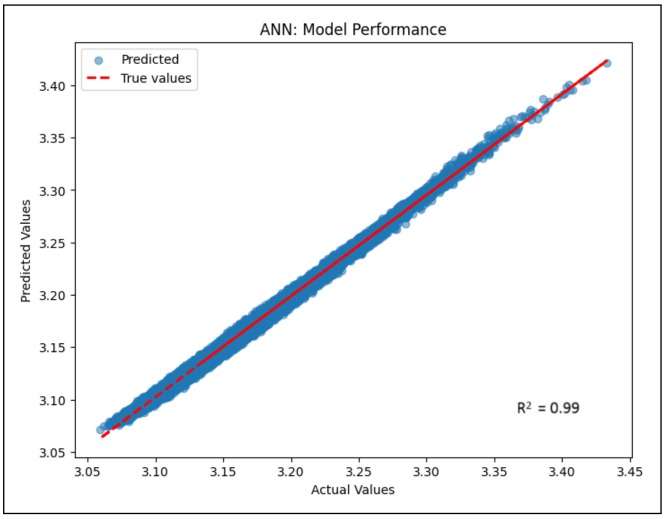

Figure 2: ANN:Model Performance

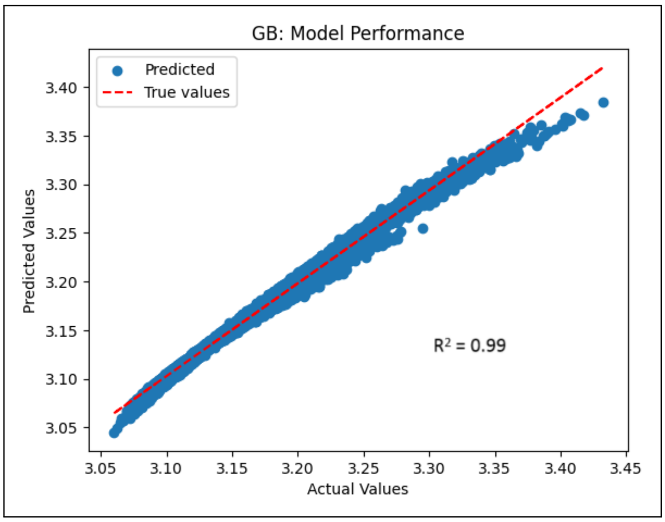

Figure 3: Gradient Boosting:Model Performance

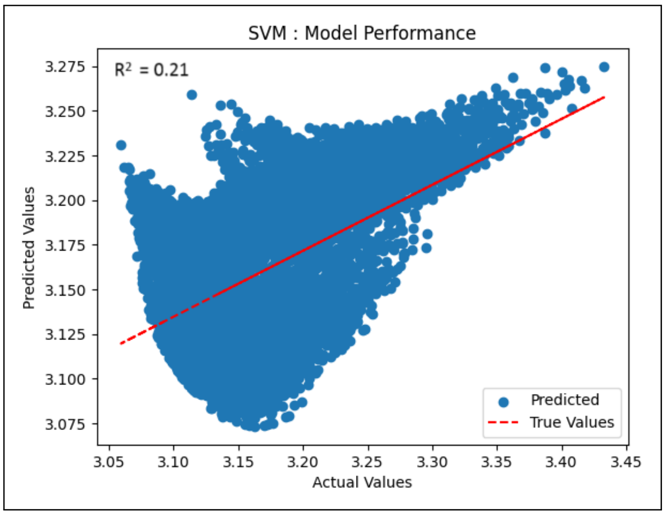

Figure 4: SVM:Model Performance

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