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Comparison of Various Machine Learning Models to Predict Factor of Safety of Gabion Walls.

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Abstract
Gabion walls are the most versatile type of retaining structure with several benefits like flexibility, eco-friendliness, economy. Like most of the retaining walls, Gabion walls are also analyzed based on coulomb's theory with conventional limit equilibrium method. This study attempted to predict the safety factor against sliding of gabion wall using widely used machine learning techniques for which 38,800 data were created using C# coding language. The datasets contains various input parameters which includes, height of the wall, wall top width, internal angle of backfill and base soil, soil density, gabion density, backfills soil angle, and inclination of the wall. Three machine learning models have been trained to predict the factor of safety of gabion walls. All these models have been validated using 10-fold cross validation technique and are evaluated based on their coefficient of determination (R^2) value, root mean square error (RMSE) and mean absolute error (MAE). In all three models' good values of these parameters have been observed. The R^2 values obtained for all the models range from 0.8708 to 0.9997. On comparison, Random Forest Method's prediction was most accurate to the computed FOS with R^2 equals to 0.9997, whereas Artificial neural network was also close with R^2 of 0.9919.

Keywords
Machine Learning, ANN, Gabion Wall, Factor of Safety, Sliding

1. Introduction

Retaining walls are often used civil engineering structures built to control slopes, stop soil erosion, and offer structural support for nearby buildings and roads. For support against lateral stresses on slopes that are vertical or almost vertical, retaining walls were most frequently used [1].Among the numerous forms of retaining walls including gravity retaining walls, cantilever retaining walls, and reinforced soil walls, gabion retaining walls have received significant attention due to several benefits like flexibility, permeability, eco-friendliness, economy, and aesthetics.

Gabion offers extreme resistance to active earth pressure without breaking or deforming [2]. Compared to other conventional solutions, these structures are environmentally friendly and have lower carbon footprint [3]. Like most of the retaining walls, Gabion wall are also analyzed based on Coulomb's classical earth pressure theory [4]. Forces likes lateral earth pressure, Weight of the retraining walls, wedge between plain sliding and frictional retaining wall are acted on the retaining walls. Moreover, external forces like earthquake surcharge load are also known to act on the walls. Even though the retaining walls have been built for a long time, the cause of their failure mechanism is not entirely known [5]. The prediction design used in current design codes is achieved utilizing limit equilibrium method.

Machine learning techniques have been widely applied in a variety of scientific, technological, and engineering disciplines [6–12]. The authors are aware of very little application of machine learning approaches for predictions in the field of gabion wall stability research. Machine learning (ML) methods and artificial intelligence techniques have been shown to be reliable in several geo-technical fields by Zhang et al. [13].

This study attempts to assess the safety factor of gabion wall against sliding using widely used machine learning techniques. Database containing 38,880 datasets were created using C# (C sharp) codes for training and validation of the machine learning models. This data includes, height of the wall, wall top width, internal angle of backfill and base soil, soil density, rock density, backfills soil angle, and inclination of the wall as input parameters and factor of safety of gabion wall against sliding as output parameter. Multiple Regression (MR), Random Forest (RF) and Artificial Neural Network (ANN) were three different machine learning models utilized to come up with prediction of the factor of safety of the Gabion wall.

2. Methodology

2.1 Stability

One of the most affordable geotechnical structures is a gabion wall because it can be built with locally available materials and blend in with its surroundings, making it both economical and environmentally benign.

Typically, the design of a gabion wall conforms to the conventional idea of retaining walls, which is founded on the limit equilibrium approach and may be separated into two components as follows:

1. Analysis of external stability for sliding, overturning, and bearing capacity, and
2. Analysis of overall stability for gabion retaining wall with shear failure slope. [14, 15]

Figure 1 displays the geometrical inputs used in the investigation. In this situation, only static loading conditions are considered, and the front offset is limited to 0.15m. The size of the Gabion used in this study is 1m×1m×1.5m. Moreover, the base of the gabion retaining wall is assumed to be strong enough to withstand bearing pressure and settlement.

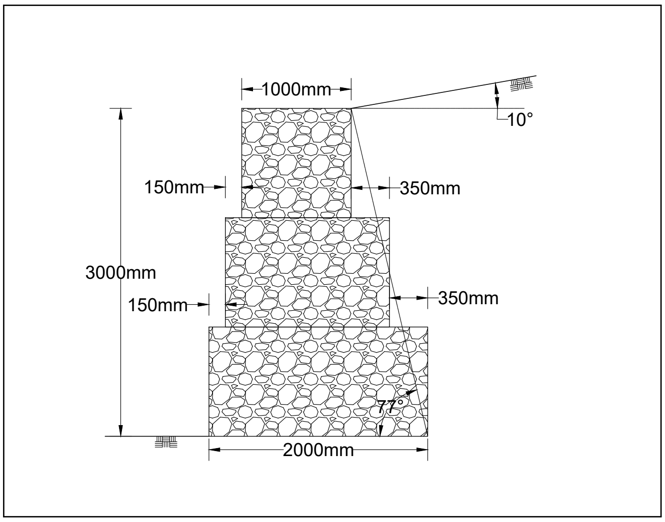

Figure 1: Geometry of a Gabion wall.

The modes of structural failure that lead to the failure of gabion boxes must be investigated in reliability-based analyses of gabion walls. In this work, such failure is not taken into account, and the emphasis is exclusively placed on uncertainty resulting from geotechnical parameters and the analysis has only been conducted for factor of safety against sliding effect. The weight forces and active forces at work in the gabion retaining walls are depicted in Figure 2. In the figure, W_g is the vertical forces and P_a is the inclining force brought on by the soil backfill. Also, X_g represent the offset in front of the gabion wall, ϵ represent the inclination of the gabion wall with vertical ,α represent the back angle of the gabion wall.

2.2 Design Approach

Following Coulomb's theory, the active earth pressure may be calculated using the formula shown below [15], which exerts a hypothetical contact between the wall and the retained Granular backfill.

$$P_a = \frac{1}{2} \times K_a \times \gamma \times H^2 \tag{1}$$

Where,
H is the height of the gabion wall
γ is the unit weight of the retrained granular soil
K_a is the coefficient of active earth pressure
The resulting pressure, P_a, is always assumed to act upon a plane that is inclined at a third of the height of the wall from its toe [16]. It is anticipated that the infill material makes up 60% of the gabion wall's unit weight. Hence a gabion wall's porosity of 40% is thought to be acceptable [3].

A complete database with 38,800 datasets of gabion walls was created to accomplish the study's goal. In this database, the internal angle of friction of the backfill soil and base soil, the inclination of the backfill, and the inclination of the gabion wall were all taken into account as input parameters, and the system's output parameter was set to be the factor of safety against sliding. Table 1 lists their unit, category, and range.

According to the sliding evaluation, there are two resistive forces and one sliding force, which is the active earth pressure force. The formulation, which assesses the FOS against sliding against various combinations, has been programmed in C# code to generate the entire dataset.

2.3 Case Example

In addition to relying on their weight to prevent sliding and overturning, gabion walls' layout also significantly contributes to stability. The usefulness of Gabion wall has increased as Gabion walls can be designed to fit a variety of shapes and sizes, making them ideal for use in several types of terrain moreover, they are environmentally friendly and can be constructed using locally sourced materials.

Among different modes of failure of gabion walls, sliding is one of the most critical modes. The most significant sliding force is lateral earth pressure acting on the back of the gabion wall. Surcharge loads present in the backfill surface can amplify this force. Therefore, 1.5 is generally taken as the minimum safety factor against sliding. Figure 1 shows the geometry of the gabion wall with different parameters involved. The factor of safety against sliding can be calculated by:

$$FOS = \frac{\sum F_R}{\sum F_O} = \frac{\sum V \tan\delta}{P_a \cos i} \tag{2}$$

Where, $\sum V$ is the total vertical force. P_a is the active earth pressure calculated by coulomb earth pressure.

From eq.1 active earth pressure

$$P_a = \frac{1}{2} \times K_a \times \gamma \times H^2$$

and, from coulomb's theorem K_a can be taken as

$$K_a = \frac{\sin^2(\beta+\phi')}{\sin^2\beta \sin(\beta-\delta)\left[1+\sqrt{\frac{\sin(\phi'+\delta)\sin(\phi'-\alpha)}{\sin(\beta-\delta)\sin(\alpha+\beta)}}\right]^2} \tag{3}$$

Where,
β is inclination of back of the wall.
ϕ' is effective angle of shearing resistance of backfill.
δ is the wall friction angle.
α is the angle of backfill.

As illustrated in figure 1, the effective height of the wall is 3m, the front offset of the wall is 150mm and back offset is 350mm. the soil profile behind the gabion wall is 10°, the value of ϕ' is considered as 30°. Wall friction is taken as $\frac{2}{3}\phi'$.From calculation, K_a is 0.477, Total horizontal force is 27.9 kN/m and sum of total vertical force is 92 kN/m. Using eq.2 FOS against sliding is 1.9.

Table 1: Input and output parameters in the dataset.

Parameters	Unit	Symbol	Category	Range
Wall height	m	H	Input	3,4,5,6,7,8,9, and 10
Wall top Width	m	b	Input	1,1.5 and 2
Internal angle of friction of backfill	Degree	ϕ'	Input	28,30,32,34,36, and 40
Unit weight of Soil	kN/m^3	γ	Input	17,17.5,18 and 19
Unit weight of fill	kN/m^3	γ_{fill}	Input	13.2,15 and 16
Internal angle of friction of base soil	Degree	ϕ_1'	Input	15,20,25 and 30
Inclination of the wall	Degree	ϵ	Input	0,3 and 6
Backfill soil angle	Degree	α	Input	0,10 and 20
Factor of Safety	FOS	-	Output	0.51-5.11

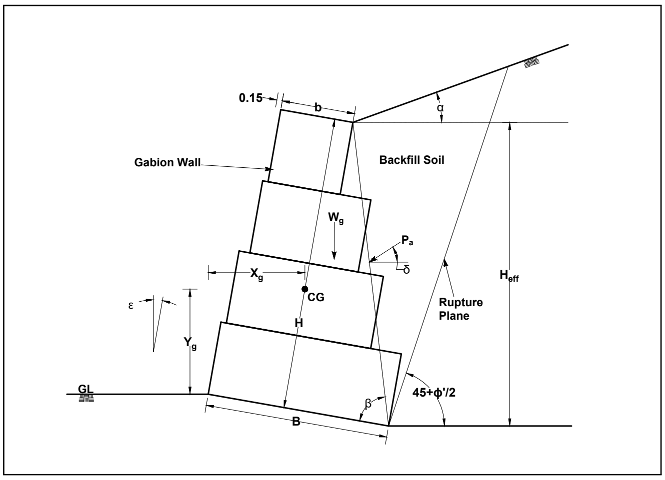

Figure 2: Forces acting on a gabion wall

2.4 Multiple Regression (MR)

The link between one dependent variable and two or more independent variables can be determined using the powerful statistical approach known as multiple regression [17, 18]. By accommodating multiple predictors and assessing their combined influence on the outcome variable, it expands on the idea of simple linear regression.MR is generally used to develop predictions about the correlations between two or more variables that have cause-and-effect relationships, using the equation [19]:

$$y = \beta_0 + \beta_1 x_1 + ... + \beta_n x_n \tag{4}$$

Where,
y = dependent variable
x_i = independent variable
β_i = parameters.

Based on the considerations described above, multiple linear regressions were performed on the datasets using k-fold cross validation technique and the model performance was assessed by evaluating the magnitude of the coefficient of determination (R^2), root mean square error (RMSE) and mean absolute error (MAE) for the regression. The scikit-learn package from the Python coding language was utilized when fitting MR Model.

2.5 Random Forest (RF)

As an effective ensemble learning tool for predictive modeling, the random forest approach has gained popularity. It emphasizes the significance of accurate prediction in various domains and highlights the limitations of traditional single tree methods. The ultimate result of the RF regression is the mean of the outputs of all decision trees. Random forest creates hundreds or even thousands of decision trees, each of which works as its own regression function. Decision nodes and leaf nodes make up each decision tree. Each sample that is fed into the decision nodes is evaluated by a test function, and then, depending on the sample's characteristics, it is passed to other branches. It is necessary to specify the number of trees (ntree) and input variables considered in each node split before creating an RF model. [20].

Let, $S_n = (X_1, Y_1), (X_2, Y_2), \ldots\ldots (X_n, Y_n), X \in \mathbb{R}^m, Y \in \mathbb{R}$ be the training set with n data where X represents the input vector of m features and Y represents the output scalar.

The decision tree's initial step requires selecting the optimal split among all the variables. Starting at the root, each node in this splitting method applies its distinct split function to the new input X repeatedly till reaching a terminal node (also known as tree leaves). The tree is typically halted after a certain number of levels have been reached or when a node has fewer observations than a predetermined threshold. After the training process is complete, a prediction function called, $h(X, S_n)$ is constructed over, S_n. The number of trees to be fitted was set at 1000 and the modeling was done using famous scikit-learn library available in Python programming language.

2.6 Artificial Neural Network

Artificial neural networks (ANNs), which are modeled after the organization and function of the human brain, are now powerful computational and predictive tools. Like the neurons in a real brain, artificial neural networks also have nodes that are connected to one another in various layers of the networks [21]. Auto correlation, multivariate regression, linear regression, trigonometric analysis, and other statistical methods may all be directly replaced by neural networks [22].

Based on supervised and unsupervised learning techniques, there are many types of ANN. . The most fundamental form of

ANN architecture is called perception architecture, which consists of one neuron with two inputs and one output. Different activation functions are used such as ReLu, sigmoid etc.. Multilayer perceptions (MLP), which have one input layer, one output layer, and one or more hidden layers are utilized for more complicated applications.

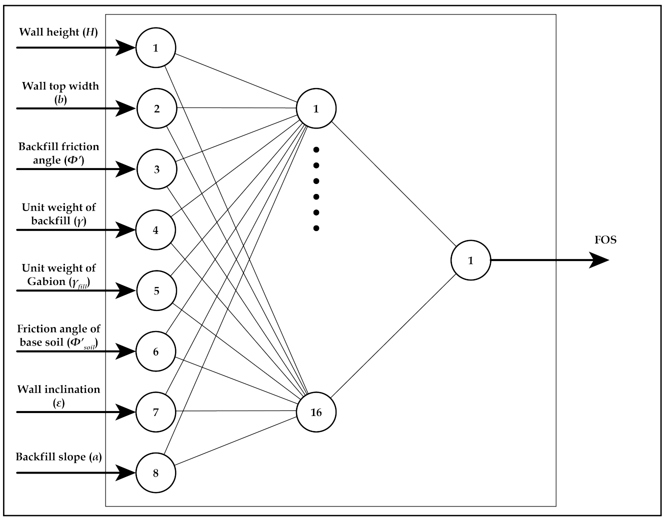

Figure 3: Model Architecture of ANN

Current study utilizes Tensorflow and scikit-learn libraries of Python codes for the modeling of ANN. The adopted model architecture contains one hidden layer with 16 number of neurons for the prediction work defined. According to research, one or two hidden layers are shown to be helpful for the majority of situations, depending on how difficult the pattern recognition challenge is [18]. The selected ANN model architecture is further illustrated by figure 3.

2.7 Cross Validation

A key aspect of machine learning is choosing a model and assessing it according to how well it performs. There is a difference between evaluating a model's attributes and evaluating those attributes to the best of its abilities. Researchers have published a variety of methods that are utilized with a variety of models. However, the ease of use and applicability of cross-validation are considered and extensively employed to choose and assess the model [23].

Given the drawbacks of conventional model assessment techniques, like using a single train-test split, the K-fold cross-validation has been used. These techniques could produce incorrect performance estimates and be vulnerable to overfitting and the unpredictability of data division. By overcoming these restrictions, K-fold cross-validation offers a more thorough and accurate assessment of the model.

Each model in this study has been subjected to 10-fold cross-validation. The dataset is divided into ten sets, each consisting of 90% training data and 10% testing data, which are then fed to each of the three algorithms independently. Each of MR, RF, and ANN's best models are selected based on parameters like MAE, R^2, and RMSE, and the models are then contrasted with one another on various scales and graphs.

3. Results

Root Mean Square Error(RMSE) ,Coefficient of Determination (R^2), and Mean Absolute Error(MAE) are computed in each model to determine the model's prediction capability. By fitting lines between observed and modeled data, the prediction skills of all produced models have been assessed. Researchers, academics, and programmers can compare and relate the performance of the various models by evaluating the model accuracy. A comparison of FOS against sliding calculated using limit equilibrium and predicted from ANN,RF,MR is presented in Figures 4 to 6. The value for each model is presented in table 2. It can be noted that the R^2 of Random Forest method is highest (i.e., 0.9997) among the other two methods which is followed by Artificial neural Network with R^2 equals to 0.9919. Moreover, RMSE and MAE also show that Random Forest method is in more agreement with the predicted value of FOS than ANN and MR.

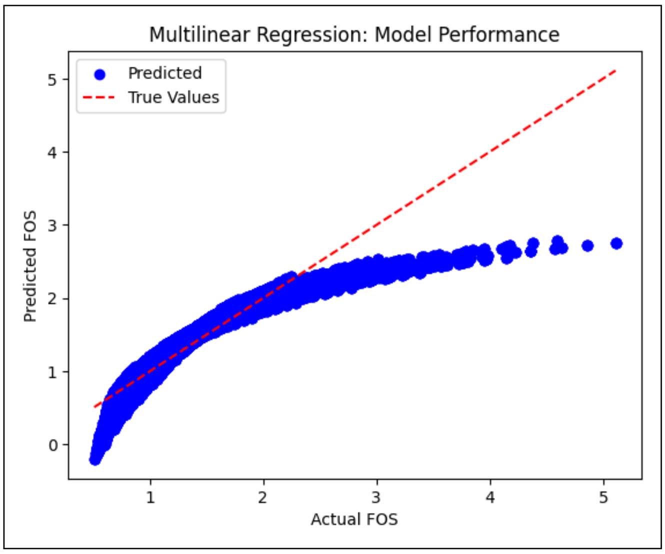

Figure 4: Predicted Vs Actual Values of MR Model

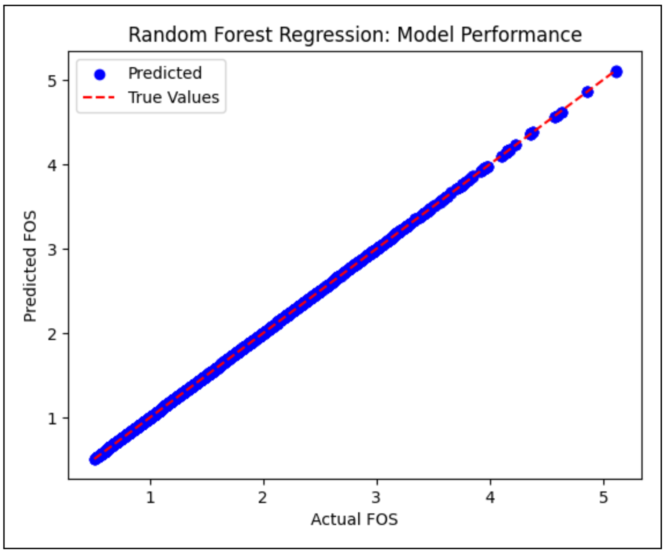

Figure 5: Predicted Vs Actual Values of RF Model

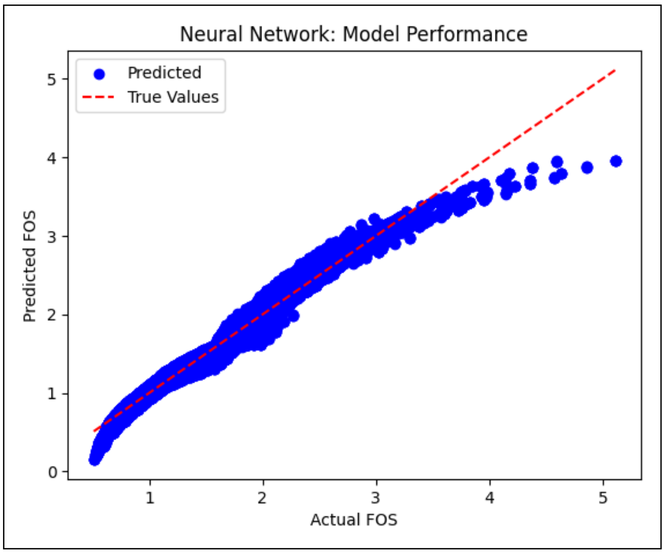

Figure 6: Predicted Vs Actual Values of ANN Model

Table 2: Performance indices (R^2, RMSE, and MAE) of the developed models.

Model	R^2	RMSE	MAE
Multilinear Regression	0.8708	0.1895	0.1248
Random Forest	0.9997	0.0085	0.0053
ANN	0.9919	0.0405	0.0366

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