

Prediction of Cantilever Retaining Wall Stability using Optimal Kernel Function of Support Vector Machine

Rohaya Alias¹

School of Civil Engineering
College of Engineering
Universiti Teknologi MARA Pahang
26400 Bandar Tun Razak Jengka,
Pahang, Malaysia

Siti Jahara Matlan²

Civil Engineering Programme,
Faculty of Engineering
Universiti Malaysia Sabah
88400 Kota Kinabalu
Sabah, Malaysia

Aniza Ibrahim³

Faculty of Civil Engineering
Universiti Pertahanan Nasional
Malaysia
57000 Kuala Lumpur
Malaysia

Abstract—The Support Vector Machine is one of the artificial intelligence techniques that can be applied to forecast the stability of cantilever retaining walls. The selection of the right Kernel function is very important so that the Support Vector Machine model can make good predictions. However, there are no general guidelines that can be used to select Kernel functionality. Therefore, the Kernel function which consists of Linear, Polynomial, Radial Basis Function and Sigmoid has been evaluated to determine the optimal Kernel function by using 10 cross-validation (V-fold cross-validation). The achievement of each function is evaluated based on the mean square error value and the squared correlation coefficient. The mean square error value is closer to zero and the squared correlation coefficient closer to the value of one indicates a more accurate Kernel function. Results show that the Support Vector Machine model with Radial Basis Function Kernel can successfully predict the stability of cantilever retaining walls with good accuracy and reliability in comparison to the various other Kernel functions.

Keywords—Cantilever retaining wall; kernel function; prediction; stability; support vector machine

I. INTRODUCTION

Cantilever retaining walls were introduced by the Burlington and Quincy Railroad in the 1880s. This retaining wall is constructed using reinforced concrete to withstand high tensile strength. It consists of two main parts namely, the walls, and the base made of reinforced concrete. Typically, the height of this wall ranges from 2.5 m to 6.0 m and is usually in the shape of either an inverted L or T. Its size is wider and flatter, and its construction cost is cheaper because the building materials are less compared to gravity walls [2]. The walls can be built on the construction site or pre-cast concrete that has been made in the factory can be used and only installed on the construction site which saves more time and energy. For heights exceeding 6 m, the use of prestressing techniques will be used. The wall part of this cantilever retaining wall is built protruding out of its large and solid site.

The cantilever retaining walls are very widely used in geotechnical engineering practice. Therefore, engineers play an important role in ensuring the construction of cantilever retaining wall is stable and safe. The stability of cantilever

retaining walls involved the checking of stability in terms of overturning, sliding, and bearing capacity. However, trainee engineers may find it difficult to get optimum stability results because of the lack of experience on the behavior of cantilever retaining walls. A prediction method using conventional mathematical models is utilized to estimate the stability of the cantilever retaining walls.

The development of studies on non-linear data analysis is growing with the revolution of the artificial intelligence (AI) methods. AI method is a great and versatile computing tool for solving complex problems, series, and its ability in identifying irregular arrangements and clusters of data. This method is popular for prediction and is able to predict the data that is non-linear, and not uniform. Among the AI methods introduced are artificial neural networks (ANN), adaptive neuro-fuzzy inference systems (ANFIS) and support vector machines (SVM).

The support vector machine (SVM) is the latest machine learning technique after neural network machine. Boser, Guyon and Vapnik introduced the SVM method in 1992 at the Annual Workshop on Computational Learning Theory. SVM is a new generation of statistical learning method which aims to recognize the data structures. It contains algorithmic learning using statistically based theories [4, 22, 15]. Learning is done by using input data and output data as the desired target this is known as supervised learning.

The SVM model has been extensively used in several fields of study for classification and prediction. Initially, SVM was developed to solve the classification problem, after which the use of SVM was extended for regression [27]. SVM regression is considered a nonparametric technique because it relies on kernel functions. According to Li et al. [6], SVM was developed as a regression device and is recognized as support vector regression (SVR). SVM is also worked to reduce overfitting and decreases the expectations of machine learning errors [26]. Smola and Scholkopf [23] stated that SVM is a method that can overcome overfitting and will result in good performance. In summary, it can be agreed that SVM is a technique that can make classifications and predictions with maximum accuracy by using the machine learning theory.

SVM method can solve regression and pattern recognition problems effectively and can also be used to make predictions and stability assessments [28]. According to Lu et al. [7], SVM has many advantages when utilized to solve small samples, nonlinear, and high -dimensional pattern recognition problems when compared to other algorithms.

II. LITERATURE REVIEW

In the last decade, the use of SVM to solve problems that cannot be solved using traditional methods in geotechnical engineering has been deeply investigated. The SVM model can improve the weaknesses found in traditional models such as ease of overfitting, single consideration factor, and inability to make predictions with long periods. Several previous studies have found that SVM is a potential method and has become the most desired in recent studies because of its ability to solve nonlinear and time series regression problems.

In the geotechnical field, reviews show that SVM is used effectively to predict soil shear strength, landslides, slope stability, deformation displacement, etc. Ly and Pham [8] proposed the use of the SVM model to predict soil shear strength using physical properties of soil as input parameters. The results of the study found that the SVM model showed good performance for soil shear strength prediction with an R value of 0.9 to 0.95. It was found that the three parameters that most influenced the prediction of soil shear strength were moisture content, liquid limit, and plastic limit. Shi et al. [21] used the SVM method to predict the deformation of the surrounding rock in the shallow-buried tunnels. The research indicates that the method of SVM produces good accuracy when utilized in making rock deformation predictions around shallow-buried tunnels. Besides, SVM is also an easy method to implement. Ramya and Vinodhkumar [18] used the SVM technique to predict the minimum factor of safety (FOS) based on upper and lower bound theorems for slope stability. The study confirmed that SVM has the capability to calculate the FOS with an adequate degree of exactness and suitable to use for the prediction of the stability of slopes. Rachel and Lakshmi [16] introduced the SVM prediction model to predict landslides by predicting rainfall data sets using big data concepts. The study summarizes that SVM is proven to be an effective technique for predicting landslides by first predicting rainfall. Samuil and Sitharam [20] compared the SVM and ANN on the liquefaction susceptibility of soil under earthquake. The research proves that SVM can produce good performance for the prediction of soil liquefaction susceptibility under earthquakes. Samui [19] investigated the effectiveness of the SVM method when compared with the ANN method to predict the frictional capacity of driven piles in clay. The results showed that SVM gave better performance than the ANN method. However, not many previous studies have been found on the use of the SVM method for predicting the stability of retaining walls. Mohamed et al. [10] used SVM to predict the external stability of segmental retaining walls reinforced with backfill with residual soil and geogrid. The results proved that the SVM based on the Radial Basis Function method and based on the specific data selection can predict the external stability factor of segmental retaining wall with a good accuracy. Cheng and Wu [3] studied the efficacy of the Evolutionary Support Vector Machine Inference Model

(ESIM) to forecast wall deformation in deep excavations. ESIM is a model that uses the SVM method and fast messy genetic algorithm (FMGA). The study found that the ESIM model successfully predicts wall deflection and deformation.

SVM provides two properties that are not found in other learning algorithms, namely the process of maximizing margins and the transformation of non-linear input space into feature space using the Kernel method [4]. Many experts have known that the capabilities of SVM are exactly correlated with Kernel function. The Kernel function transforms a data set into a hyper-plane [13]. Additionally, kernel variables need to be calculated accurately because it determined the structure of high dimensional features when the final solution was performed. Commonly, the types of Kernel functions found in the SVM model are Linear, Polynomial, Gaussian or Radial Basis Function (RBF), Laplace, Sigmoid, Exponential, etc. [9]. The Linear Kernel used when data is linearly separable. The Polynomial Kernel is well suited for problems where all the training data is normalized. The RBF and Laplace Kernel used when there is no prior knowledge about the data. The Sigmoid kernel used as the proxy for neural networks [24].

An accurate prediction model can be obtained by using the optimal Kernel functions. However, there are no general guidelines that can be used to select Kernel functionality. Based on the previous studies, it was found that most of the research conducted until recently has focused on the advantages of the SVM models. Very few studies were conducted to obtain the right Kernel function. Nanda et. al [12] conducted termite detection studies using different Kernel functions in support vector machines and found that Polynomial Kernel has produced the best accuracy. Hong et. al [5] compared the effectiveness of four Kernel functions in a support vector machine in a landslide mapping study. Findings emanated from the research indicated that the SVM-RBF model is the most suitable for landslide susceptibility assessment.

Therefore, this study intends to compare the Kernel function model between Linear, Polynomial, Radial Basis Function (RBF), and Sigmoid in their ability to predict the cantilever retaining walls stability and suggest the optimal Kernel function among them. Only four types of Kernel functions were selected since it was most frequently used compared to other Kernel functions and produced satisfactory results.

III. METHODOLOGY

The Statistica software was used to develop SVM models using data mining methods. According to Thuraisingham [25], Radhakrishnan et al. [17] and Mohammed and Wagner [11], data mining is a process of answering all questions and identifying information, forms and trends found in large quantities of data. Furthermore, in the use of data mining, there are various techniques that can be used to help make decisions. In this study, machine learning techniques have been used for SVM model making predictions. SVM model prediction is performed using input and output data. The data used for this study were 280 different designs of cantilevers retaining wall designs. The input parameters used for prediction contains walls of various heights, slope angles, and surcharges. On the

other hand, the output parameters involve the external stability of the retaining wall i.e., the safety factor (FOS) for sliding, overturning, and bearing capacity. The output parameters are applied as a target for the model prediction.

A. Kernel Function Selection

The selection of the right Kernel function is very essential so that the SVM model can make a good performance. Basically, SVM is employed as a quadratic optimization to solve the case of linear classification. Applying Kernel functions which are presented into the combined type of the optimization model can easily expand linear to nonlinear SVM via of functional mapping [14]. SVM uses a technique called the Kernel trick to provide a bridge from linear to nonlinear. The equation of Kernel trick is shown in equation (1).

$$K(x, y) = \langle f(x), f(y) \rangle \quad (1)$$

Where K is the Kernel function, x and y are n-dimensional inputs, and f is a map from n-dimension to m-dimension space.

In this study, Kernel function consisting of Linear, Polynomial, Radial Basis Function (RBF) and Sigmoid function was evaluated to determine the best Kernel function by using 10 cross-validations (V-fold cross-validation). Based on the mean square error value (MSE) and the squared correlation coefficient (R^2), the achievement of each function is determined. The MSE measures the differences in values between the target data and the predicted data in the existing predicted models. The MSE value is closer to zero and the R^2 value is closer to the value of one indicates a more accurate Kernel function. The equations of MSE and R^2 for the performance evaluation of the prediction model are shown in equation (2) and equation (3) as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \tilde{y}_i)^2 \quad (2)$$

Where n is the total of data points, y_i is the target data, and \tilde{y}_i is the predicted data.

$$R^2 = \frac{(\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y}))^2}{\sum_{i=1}^n (x_i - \bar{x})^2 \sum_{i=1}^n (y_i - \bar{y})^2} \quad (3)$$

Where n is the total of predicted data, x_i is the target data, y_i is the predicted data, \bar{x} is the average of target data series, and \bar{y} is the average of predicted data series.

B. Optimum Parameters Selection

The Epsilon-RBF model was used to obtain the optimum model parameters such as gamma, capacity, epsilon, and Nu parameters. The optimal use of parameters in the Kernel function will produce an accurate prediction model [1]. The most common method used to obtain optimal model parameters is through the 10-cross-validation method (V-fold cross-validation). The cross-validation method is used in SVM to check the overfitting of data and it gives more correct predicted results.

C. Model prediction

All machine learning algorithms must be tested and validated to select those with the highest performance and prediction accuracy. After obtaining the optimal model parameters, the data set was randomly divided by 70% for the

training and 30% for the testing. To speed up training time, a selection of training data was used. Only training data close to the boundary was used. Data far from the boundary were eliminated to shorten training time.

SVM algorithm attempt to predict a target data or known as a dependent variable using features, which is the dependent variable. Prediction is implemented by mapping an independent variable to a dependent variable known as a process mapping function. The process of a mapping function for an SVM is a boundary that distinguishes two or more classes.

After getting all the prediction output, root mean squared error (RMSE) and regression square was computed for every model and compared. The root mean squared error (RMSE) can be obtained from equation (4).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \tilde{y}_i)^2} \quad (4)$$

Where n is the total of data points, y_i is the target data, and \tilde{y}_i is the predicted data.

IV. RESULT AND DISCUSSION

Kernel functions consisting of Linear, Polynomial, Radial Basis Function (RBF) and Sigmoid function were evaluated in the SVM model analysis. The results show that the Kernel function plays an important role in producing a good SVM model. The Kernel functions have the advantage of converting nonlinear input space to linear feature space. Table I and Table II show a comparison of the prediction performance of the SVM model based on MSE and R^2 values for the external stability safety factors using four different Kernel functions. The RBF kernel was found to produce the best prediction accuracy for the external stability factor of cantilever retaining wall, with the MSE value being closest to zero and the R^2 value being closest to one. This finding seems to be agreed with the study conducted by Hong et. al [5], where the RBF Kernel showed better performance than other Kernel functions. Followed next by the Linear, Polynomial, and finally the Sigmoid function which produces the least accurate prediction. Therefore, the Radial Basis Function (RBF) was chosen to be applied to the SVM model for all the external stability safety factors of the cantilever retaining wall.

TABLE I. THE PERFORMANCE OF THE SVM MODEL BASED ON MSE VALUES USING FOUR KERNEL FUNCTIONS

External Stability	Linear	Polinomial	RBF	Sigmoid
FOS for sliding	2.071	7.156	0.396	684.920
FOS for overturning	12.844	37.771	2.187	1930.534
FOS for bearing capacity	0.089	0.153	0.050	6.832

TABLE II. THE PERFORMANCE OF THE SVM MODEL BASED ON R^2 VALUES USING FOUR KERNEL FUNCTIONS

External Stability	Linear	Polinomial	RBF	Sigmoid
FOS for sliding	0.955	0.840	0.992	0.264
FOS for overturning	0.914	0.747	0.987	0.264
FOS for bearing capacity	0.708	0.478	0.716	0.479

A. SVM Model Prediction

Prediction of the cantilever retaining wall stability using the SVM model was performed by implementing the RBF Kernel and the optimal gamma, capacity, epsilon, and Nu parameters. The prediction accuracy of SVM model was compared based on the RMSE and R^2 values. Table III shows a comparison of RMSE and R^2 values for the external stability safety factors. It can be clearly observed that the prediction of the cantilever retaining wall stability using the SVM model with RBF Kernel function for safety factor of overturning is more accurate because it produces an RMSE value that is closer to zero and an R^2 value that is closer to one.

TABLE III. THE PERFORMANCE OF THE SVM MODEL USING RBF KERNEL FUNCTION BASED ON RMSE AND R^2

External Stability	RMSE	R^2
FOS for sliding	0.172	0.9985

FOS for overturning	0.044	0.9992
FOS for bearing capacity	0.236	0.9766

The prediction results in terms of the comparison of target with predicted output for the safety factor of sliding, overturning, and bearing capacity are shown in Fig. 1. It seemed that the target together with predicted output values were mostly overlapping for safety factors of sliding and overturning because of a very good prediction result of R^2 which is 0.99985 and 0.9992, respectively. The most significant difference of target and output values can be seen at the FOS for bearing capacity.

Fig. 2 presented the R^2 plot for a safety factor of sliding, overturning, and bearing capacity. The results proved that the SVM based on the RBF Kernel function can predict the cantilever retaining wall external stability with a good accuracy and reliability because the R^2 value greater than 0.97. The graph shows the dots were scattered close to the 45° line.

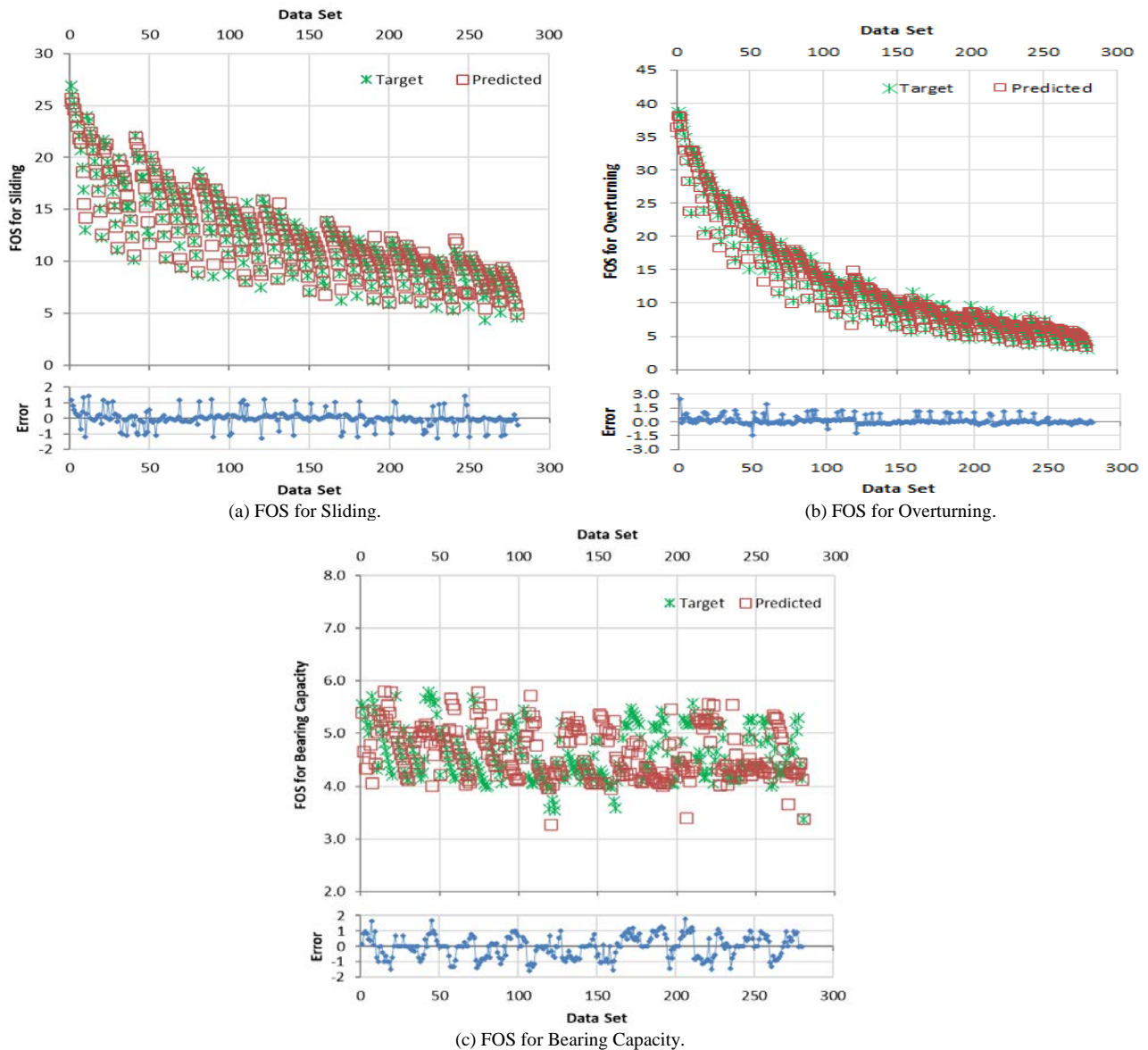


Fig. 1. Comparison of Target with Predicted Output for a Safety Factor of (a) Sliding, (b) Overturning, and (c) Bearing Capacity.

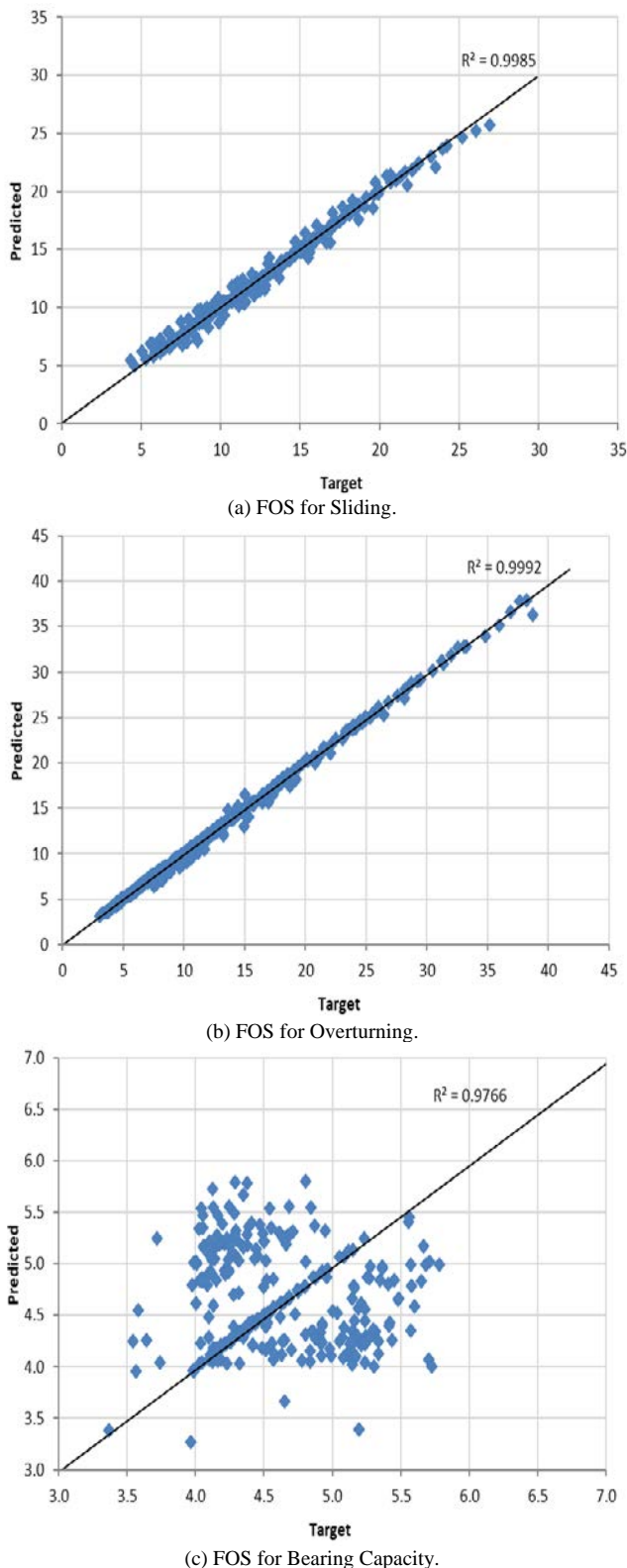


Fig. 2. Regression Square (R^2) Plot for a Safety Factor of (a) Sliding, (b) Overturning, and (c) Bearing Capacity.

V. CONCLUSION

SVM model prediction based on four Kernel functions, namely Linear, Polynomial, Radial Basis Function (RBF) and

Sigmoid were applied successfully to predict 280 data sets of external stability factors for cantilever retaining walls. The perfect prediction result was for RBF Kernel if compared with the other Kernel function because of the good R^2 for the output value. SVM model prediction based on RBF Kernel was able to predict the cantilever retaining wall stability with good accuracy and nearly to the target data. The prediction of the external stability of the cantilever retaining wall using the SVM model has successfully produced an accurate prediction by performing nonlinear regression for high-dimensional data sets.

As a conclusion, the results of the study can contribute to researchers for the current literature, especially in the field of retaining walls stability with the SVM approach. The optimal solution found in this study is that the right Kernel function has been obtained for the SVM model by producing the best prediction accuracy for the external stability of the cantilever retaining wall. The SVM is a technique that can solve complex problems with the application of appropriate Kernel functions. This study can help to forecast the stability of cantilever retaining walls used in civil engineering problems quickly and accurately. Prediction model developed provides advantages to geotechnical engineers in producing a more stable, and safe cantilever retaining wall.

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