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Application of support vector machine in geotechnical engineering: A review

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Abstract

Support Vector Machine (SVM) is an advanced machine learning technique grounded in statistical theory, designed to address both linear and non-linear classification and regression problems. In recent years, SVM has gained significant traction in diverse domains of geotechnical engineering, such as foundation engineering, slope stability analysis, soil-structure interaction, and tunnel analysis. A thorough review of the existing literature reveals that SVM has been applied effectively across various sub-disciplines of geotechnical engineering, demonstrating its versatility and capability to handle complex data sets and problems that traditional methods struggle with.

Conventional geotechnical analysis techniques, including the finite element method, limit equilibrium method, and upper bound limit analysis, often fall short in dealing with the intricate, non-linear relationships present in soil-structure interactions. These traditional approaches are largely grounded in linear relationship frameworks, which limits their effectiveness in capturing the complexities of real-world geotechnical scenarios. This paper aims to provide an extensive review of the strengths, applicability, and diverse applications of SVM within the field of geotechnical engineering. It will explore how SVM can not only be utilized efficiently in existing methodologies but also be enhanced through integration with other optimization algorithms. By doing so, this review seeks to offer valuable insights into the potential improvements and innovative directions for SVM applications, paving the way for more robust solutions in geotechnical challenges.

Keywords: Support Vector Machine; Slope Stability; Foundation; Machine Learning; Kernel Function; Radial Basis Function

1. Introduction

Support Vector Machines are supervised learning models, a machine learning algorithm presented by Vapnik [1995] [1], based on the statistical learning theory used to perform regression and classification analysis. The objective of the SVM algorithm is to find the largest margin between two classes by a hyperplane (fig.1). SVM utilizes the concept of mapping the data into a high-dimensional space where linear classification is carried out. The Support Vector Machine algorithm is developed from the optimal problem of the classification hyper-plane under the linearly separable condition. The concept of the algorithm is to maximize the interval of the training set and minimize a bound on the generalization error of a model, rather than minimizing only the mean square error over the data set [2]. The kernel functions (polynomial, linear, radial basis function, sigmoid) makes SVM more flexible and able to handle non-linear problems, therefore, SVM is also used for classifying non-linear regression problems by introducing Ɛ-insensitive loss function [3], [4]. Support Vector Machine implements the Structural Risk Minimization Principle (SRMP), which has shown to be superior to more traditional Empirical Risk Minimization Principle (ERMP), employed by many of the other modeling techniques [5].

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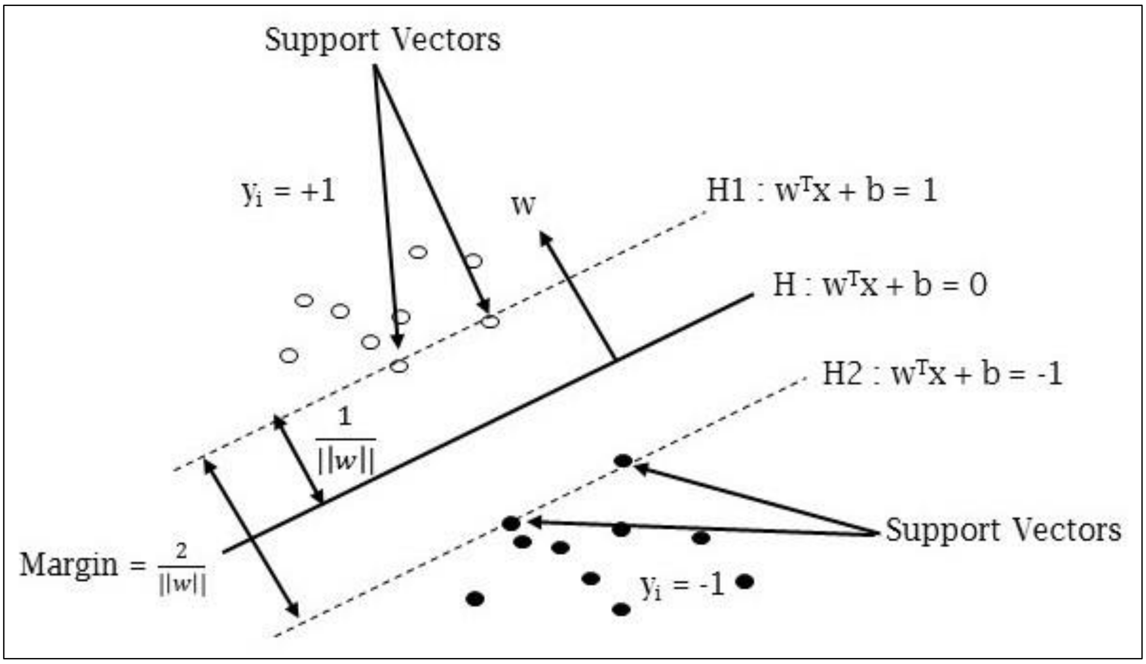

Figure 1 Schematic Representation of LSM Process

With SRMP, SVM can get decision-making rules and achieve small error for independent tests set and hence can solve the learning problems efficiently [6]. SRMP produces better generalization than traditional techniques as it minimizes an upper bound of the generalization error, whereas ERMP minimizes training error. On the other hand, the optimization algorithm of SVM has the ability of solving linearly constrained quadratic programming functions leading to an optimal, global and unique solution [7]. Thus, SVM is an efficient novel approach to improve the generalization performance and can attain a global minimum. Due to its simplicity, SVM technique has been used in various applications including Image Recognition [8], Text categorization [9], Speech Recognition [10] and Cancer detection [11]. When compared to Artificial Neural Network (ANN), SVM uses its algorithm to determine support vectors rather than by trial and error, which has been used by ANN in determining the hidden nodes.

Due to its good performance, attractive features and strong theoretical statistical framework, SVM is gaining popularity in several fields, especially for noise-mixed data. In recent years, SVM has been successfully applied in regression, classification and forecasting problems, as they include techniques and aspects from machine learning, optimization, statistics and mathematical analysis. SVMs are also suitable for the classification of small samples of data as they possess good generalization performance, strong adaptability and optimization. The application of these techniques in various fields of geotechnical engineering has come a long way. This paper aims at discussing the applications of SVM and hybrid models along with challenges for future studies in geotechnical engineering.

1.1. Applications in Geotechnical Engineering

Due to the non-linearity behavior in the mechanical properties of soil and rock, the analysis becomes complex due to multivariable dependencies. In geotechnical engineering, the materials show uncertain behavior in the complex formation of materials. Therefore, in some geotechnical engineering problems, the objective function is non-convex and discontinuous. Thus, to overcome this limitation global optimization solution is of interest which will be a powerful optimization method.

There are various traditional analysis methods such as the discrete element method, finite element method [12]–[15], limit equilibrium method [16], [17], upper bound limit analysis [18]–[20] etc. that are based on linear relationship models to study the properties of soil and rock. Thus, to solve such complex and non-linear problems, the machine learning technique comes into play which is able to deal with the non-linearity behavior of soil and rock effectively by avoiding any weaknesses that may be caused by using traditional methods. SVM has proven to be the best machine learning technique which is able to solve both linear and non-linear problems effectively. The various SVM studies carried out in geotechnical engineering are discussed below.

1.1.1. Slope Stability/Landslide Analysis

Instability of slopes is a major concern in geotechnical engineering. The slope failures are one of the most frequent disasters that occurs in mountainous regions leads to loss of life, damage to property and economic loss. The slope failure may occur due to single factor or by a combination of different factors including slope properties, development of weak zones, slope geometry, seepage conditions and heavy rainfall [21].

The application of SVM in slope stability analysis is to find out the most effective function using different kernel functions in predicting failure susceptibility zones. To produce landslide susceptibility maps, different approaches have been utilized including quantitative and qualitative methodologies. The former can be divided into three categories : artificial computational techniques, statistical analysis and geotechnical engineering approaches [22]–[26] whereas the latter depends on expert's judgment as it is a subjective concern. Support Vector Machines are kernel-based machines [27], [28] that are widely used in classification and regression, as they can deal with continuous and discrete data. SVM has few parameters to adjust [29], hence is more suitable for complex and high-dimensional data. SVM overcomes the disadvantages of ANN [30] and is widely used in landslide susceptibility mapping.

Yao et.al (2008) [31] conducted study between one-class svm and two-class svm (RBF function) for LSM. The results were compared with logistic regression. They concluded, two-class svm performed slightly better based on validation by Landslide Risk. Yilmaz et.al (2010) [32] conducted a comparative study between different methods such as conditional probability (CP), logistic regression (LR), artificial neural networks (ANNs), and support vector machine (SVM) using ArcGIS and MATLAB software. They concluded, ANN and SVM performed similarly with the same accuracies. Chen et.al (2016) [33] carried out a comparative study between different svm kernels (rbf, polynomial, linear and sigmoid), to produce reliable susceptibility maps using GIS-based support vector machine (SVM) models for the Qianyang County of Baoji City, Shaanxi Province, China. ENVI software used for analysis and later visualized in ArcGIS. Based on AUC values, RBF-SVM gave better results.

Samui et.al (2011) [34] investigated the capability of LS-SVM in developing regression and classification model for slope stability analysis and compared the same with ANN. An effort is made in developing the regression and classification model where factor of safety (FS) and slope status is used as an output respectively. The optimal parameters of LS-SVM, 'Υ' and 'σ' were obtained by trial and error. Based on R, RMSE and MAE score, LS-SVM gave better results than ANN. The results of LS-SVM were also compared by SVM and RVM developed by [7], [35]. The performance of LS-SVM is slightly better than SVM but similar to RVM.

Li et.al (2014) [36] studied the application of GA-SVM for landslide prediction. GA is used for optimal parameter optimization. Single and multi-factor GA-SVM models were built. Based on RMSE, multi-factor GA-SVM performed better. Feizizadeh et.al (2017) [37] carried out a comparative study using four kernel functions in SVM for comparing the predictive performance of GIS-based landslide susceptibility mapping (LSM) for the Izeh basin, located in the eastern part of Khuzestan province, Iran. The objective of LSM is to predict future slope failures and mass movements. LSM also helps in assessing any landslide-susceptible regions in order to minimize the unpleasant consequences. In this research, SVM has been used to identify the most effective function for LSM by applying different kernel functions. Based on validation done using two separate estimators (i.e.RMSE and PBIAS) for each SVM kernel function (linear, polynomial, RBF and sigmoid), the RBF-based landslide susceptibility map yields the most accurate prediction and is identified as efficient kernel function for LSM. Hong et al. (2017) [38], studied the landslide susceptibility of Suichuan, a mountainous region at Jiangxi province in Central China. This study carried out a comparative analysis among four kernel functions of SVM : RBF, polynomial, sigmoid and linear of 178 dataset of which 70% (125) were randomly selected for training and 30% (53) were used for model validation. The receiver-operating characteristic curve (ROC) and area under the curve (AUC) were used to evaluate the performance of the model. The study concluded that the SVM-RBF model was suitable for landslide susceptibility assessment. In landslide susceptibility, out of different kernel functions, RBF has proven to be a precise predictor function.

The application of SVM is gaining popularity in hazard mapping and slope stability analysis as researchers started integrating PSO for a more effective solution to increase their accuracy without affecting computational time. Xue et al.(2014) [39], employed hybrid model, a combination of support vector machine (SVM) and particle swarm optimization (PSO) for slope stability estimation. The objective of PSO was to select the appropriate parameters for SVM to enhance accuracy. To verify the effectiveness, the model was compared with Grid Search Algorithm (GSA). GSA has a major advantage as it avoid attributes with greater numeric ranges. The study concluded, PSO-SVM to be powerful prediction hybrid tool for slope stability estimation.

Particle Swarm Optimization (PSO) was first proposed by Eberhart and Kennedy [40] is an intelligent algorithm originated from Swarm Intelligent (SI) systems. The SI systems are inspired by the foraging behavior of birds. In PSO, each particle is adjusted according to the targeted values of themselves and the swarm. The iteration continues until all particles converge to an optimal solution. Zhoa (2021) [41] carried out a comparative study between SVM and PSO-SVM for landslide susceptibility mapping. They used grid units and slope units to divide the territory into a regular square and independent slopes respectively were considered as computing units for analysis and comparison. The Grid Search Algorithm was used to find optimal parameters of SVM, which is penalty factor C and kernel parameter Y. ROC curve was adopted for the accuracy of models, concluding the accuracy of the PSO-SVM model based on slope units gave higher accuracy compared to other models (SVM model based on slope units, SVM model based on grid units and PSO-SVM model based on grid units).

Ballabio et al. (2012) [42], carried out the landslide susceptibility modeling for the Staffora river basin , an area of about 275 km^2 belonging to the northern sector of the Apennines. The SVM technique was utilized for the prediction of landslide susceptibility using ROC, success, and prediction rate curves to assess the validity of the model. Out of 20% susceptible area, 78% was identified as occurrence for the cross-validation set. Cross-validation identifies how accurately a predictive model will perform. The final susceptible map was compared with other maps analyzed by other machine learning techniques such as linear discriminant analysis, logistic regression and naive bayes classifier. The SVM technique found to be more accurate than other techniques, as the map produced by SVM has lower spatial variability for superior prediction performance.

1.1.2. Foundation Analysis

In general, the application of SVM in pile foundation is used to predict the axial pile capacity and bearing capacity of pile. Pal et al. (2008) [43], applied the SVM regression approach to model the static pile capacity from dynamic stress-wave data. A dataset of 105 dynamic stress-wave dataset was used for predicting pile capacity. The SVM regression used two kernel functions - RBF and polynomial and compared with the generalized regression neural network approach. The results showed the correlation coefficient achieved by RBF and polynomial SVM were 0.964 and 0.962 whereas the generalized regression neural network achieved 0.977. The study concluded, GRNN is more accurate compared to SVM, however, SVM is still competent.

Samui (2008) [44] investigated the potential of SVM in the prediction of friction capacity (f_s) of driven piles in clay. An approach towards developing a regression model for RBF and polynomial kernels were made and compared with ANN. Based on R-value, RBF-SVM model outperformed ANN.

A study carried out by Samui (2011) [45] using SVM regression for predicting bearing capacity of pile (Q) from pile load test data by introducing Ɛ-insensitivity loss function. Since the behavior of soil under pile load is non-linear, thus to solve such problems inclusion of Ɛ-insensitive loss function is obligatory. Ɛ-insensitive loss function measures how close the estimated values are from actual measurements. The dataset consist of 28 experimental results. The features used in SVM model were penetration depth ratio (l/d), mean normal stress (σ_m) and no. of blows (n) for predicting bearing capacity of pile (Q). The input (features) and output parameters were represented as x = [l/d, σ_m, n] and y = [Q]. Four kernel functions (polynomial, RBF, spline and Bspline) were used in the analysis. Before the data is trained, it was scaled between 0 and 1. The values of C, Ɛ and kernel-specific parameters were chosen by the trial-and-error method. In this study, sensitivity analysis was also done to identify the effective relationship between inputs and outputs of the SVM model, indicating 'l/d' as the most important factor affecting 'Q'. The study concluded, out of four kernel functions, polynomial kernel performed slightly better than others with an error of 18.46% compared to ANN model (19.1%).

SVM being highly potential is used to solve complex problems. The applicability of SVM regressor is successful in predicting ultimate bearing capacity and settlement of shallow foundation in cohesionless soils. A study carried out by Samui (2007) [46], for the settlement of shallow foundation on cohesionless soils using SVM regression technique by introducing an Ɛ -loss function. Three kernel functions were compared (polynomial, RBF and spline) to thoroughly analyze the dataset to determine which parameter is having the maximum influence on settlement. The performance of SVM model was evaluated by different combination of C and Ɛ values, using root-mean-square error (RMSE), coefficient of correlation (R) and mean-absolute-error (MAE). It is concluded that RBF kernel (C =20,Ɛ = 0.02, R= 93.20%, MAE = 6.2695mm and RMSE = 9.3839mm) found to be better in predicting settlement of shallow foundation in cohesionless soils.

Samui (2012) [47] conducted a comparative study between SVM and RVM in predicting the ultimate bearing capacity of shallow foundation in cohesionless soils. RVM (Relevance Vector Machine), is based on Bayesian treatment of a generalized linear model that chooses sparse basis sets using 'Automatic Relevance Determinations'. RVM covers all disadvantages encountered by SVM such as the requirement to estimate a trade-off parameter, absence of probabilistic outputs and need to utilize 'Mercer kernel function' [48]. RVM also uses fewer kernel functions compared to SVM. Five input parameters (depth of footing(d), width of footing (B), unit weight of sand (ϒ), footing geometry (L/B) and shearing resistance (Φ) were used to predict ultimate bearing capacity (q_u) of shallow foundation. In modelling, SVM used three tuning parameters (σ, C and Ɛ) whereas RVM used only one tuning parameter (σ). The study concluded, RVM (R=0.998) performed slightly better than SVM (R=0.996). The SVM model produced more sparse solution than RVM. Sparness of model means, producing computationally efficient and compact models that are simple and produce smooth functions.

Zhou et.al (2017) [42] conducted a study for predicting safety risks in Deep foundation pits in Subway infrastructure projects using SVM. An approach towards developing a risk prediction model is done that involves the following steps: (1) identification of risk factors from industry experts; (2) processing of the sampled data; and (3) training and testing. To validate the model, a case study of Wuhan Rail Transit Network Metro Line 7 at the Changfeng station, China was taken in study. It is concluded, the SVM gave remarkable results in assessing safety risks.

Li et.al (2019) [49] developed single and multi-point measurement Least Square (LS)-SVM models for analysis of foundation pit slope displacement. The study included the case study of Guo Hua project, China, where these models were implemented and the comparison in results were made. Based on MAE and MSE score,it is concluded the single point LSSVM over-performed another model.

1.1.3. Soil Mechanics

The application of SVM in soil mechanics has encountered with some problems such as the prediction of physical properties of soil, soil quality assessment, liquefaction potential, soil-structure interaction, and determination of consolidation parameters.

A comparative study was conducted by Gill et.al (2006) [50] for the prediction of soil moisture using SVM and ANN of The Little Washita River Experimental Watershed (LWREW) in Southwest Oklahoma of the United States. Three approaches were done to train the data. In Approach 1, soil moisture and meteorological data (air temperature, relative humidity, average solar radiation and soil temperature) were taken. In Approach 2, meteorological data was taken. In Approach 3, soil moisture data was taken. All three approaches were done for the time series 't-1' and 't'. Soil moisture is predicted for the time series 't+4' and 't+7' for different SVM kernels. Based on trial and error, the optimal SVM parameters C, Ɛ and ϒ were selected for testing the model. The study concluded, RBF-SVM to be the best-performing model.

Pal (2006) [51] investigates the potential of SVM to assess the liquefaction potential from Standard Penetration Test (SPT) and Cone Penetration Test (CPT). Two kernel functions, RBF and Polynomial were taken in analysis. The optimal parameters of both kernels were obtained by trial and error as shown in table 1.

Table 1 SVM Optimal Parameters

	RBF	**Polynomial**
SPT	C = 100 ; ϒ = 0.05	C = 100 ; d = 2
CPT	C = 100 ; ϒ = 0.6	C = 100 ; d = 2

The model accuracies for SPT and CPT are 96.15% and 97.14% respectively. When compared with neural network model [52], SVM gave better results.

Besalatpur (2012) [53] carried out a comprehensive study between optimized SVM with SA (Simulated Annealing) algorithm for predicting shear strength of soil and soil aggregate stability properties. SA algorithm helps in discovering good quality solutions to an optimization problem by trying random differences of the current solution. The parameters having greater influence on the performance of SVM model are chosen using SA algorithm. A total of 160 samples dataset used for the study. The indicator properties for determining soil aggregate stability were mean weight diameter (MWD) and geometric mean diameter (GMD) of aggregates whereas for soil shear strength, in-situ surface soil shear strength (SSSS) using shear vane under saturation condition. The Multiple-linear Regression (MLR) model used in dataset is shown in Eq(1).

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots\ldots + \beta_n X_n \qquad \ldots\ldots\ldots\ldots\ldots(1)$$

where, Y is dependent variable; $\beta 0$ is constant and $\beta 1$, $\beta 2$ .....βn are regression coefficients. SAS statistical software was used to derive MLR models. The study concluded, the optimized SA-SVM model performed much better than MLR.

Liu (2016) [54] conducted a study for soil quality assessment using support vector machine. The overall goal of the study was to develop SVM-based classification model that combined two individual models in one for better assessment. Two parameters (soil heavy metal and soil fertility) were used to predict soil quality (IA, IB, IC, IIA, IIB, IIC, IIIA, IIIB, IIIC). IA indicates the best soil quality whereas IIIC refers to the worst soil quality. Two separate models SHM-SVM (Soil Heavy Metal-SVM) and SF-SVM (Soil Fertility-SVM) were trained and merged to predict soil class. The study concluded, SQ-SVM (Soil Quality-SVM) classified with an accuracy of 98.33%.

Samui et al. (2008) [55], examined the potential of SVM for the determination of OCR of clay deposits from piezocone penetration test data. Five parameters (corrected cone resistance (q_t), vertical total stress (σ_v), hydrostatic pore pressure (u_o), pore pressure at the cone tip (u_1) and pore pressure just above the cone base (u_2)) were used for prediction. Sensitivity analysis was carried out on trained model to determine the most significant input variables to predict OCR. Different C and Ɛ combinations were performed for training dataset. The optimal value of C and Ɛ at which the highest accuracy of 89.4% obtained are 0.06 and 0.01 respectively using RBF kernel function. The study proves SVM as a powerful tool in predicting OCR.

Kovacevic et.al (2010) [56] studied the application of machine learning techniques in the prediction of soil properties and soil type classification based on known physical and chemical properties. Four machine learning techniques were used in the analysis, Linear SVM (LSVM), Gaussian SVM (GSVM), Logistic Regression (LR) and Multinomial Naive Bayes (MNB) for preparing classification and regression models. The performance of the models were evaluated using F1 score and kappa statistics (ƙ) for classification model and normalized root mean squared deviation (NRMSD) and R^2 for regression model. The study concluded, LSVM and GSVM gave best results for classification and regression models respectively.

Das et.al (2012) [57] conducted a comparative study between SVM and ANN in prediction of field Hydraulic Conductivity of clay liners. Numerous factors such as compaction characteristics, lift thickness, number of lift, and soil classification tests like Atterberg's limits and grain size were taken into consideration for the study. Based on RMSE and R score, SVM model out-performed ANN.

A comparative study conducted by Kennedy et.al (2015) [58] between three machine learning techniques, SVM, RF and ANN for prediction of Soil Organic Carbon (SOC) in Eastern Mau Forest Reserve, Kenya. Three features were taken into analysis, Climate Change (rainfall and temperature), Elevation data from DEM (curvature, slope, aspect and Topographical Wetness Index (TWI)) and Normalized Difference Vegetation Index (NDVI) from Landsat 8 Operational Land Imager (OLI). Softwares such as ArcGIS® 10.1, ERDAS IMAGINE® 2013, Microsoft Excel® 2010, Weka 3.6, and R 3.0.1 were used for Data preparations, analyses, and geovisualization. Based on RMSE and R^2, SVM out-performed other ML techniques.

Hanandeh et.al (2022) [59] conducted comparative analysis of machine learning techniques (support vector machine, Decision Trees, and Quadratic Discrimination Analysis (QDA)) for liquefaction assessment based on CPT data. For preparing supervised models, three different soil characterization datasets were selected. The first input data consists of the Mean Grain Size (D_{50}), Measured CPT Tip Resistance (q_c), Earthquake Magnitude (M), and Cyclic Shear Resistance (CSR). The second input data consists of employed D_{50}, Normalized CPT Tip Resistance (q_{c-1}), M, CSR and the third input data consists of D_{50}, q_{c-1}, M, the Maximum Ground Acceleration (amax), Effective Vertical Overburden Stress, and Total Overburden Stress. Based on significance feature analysis, the most important feature for assessing liquefaction for model 1 is measured CPT Tip Resistance, model 2 is normalized CPT Tip Resistance, and in model 3, is measured CPT Tip Resistance. They obtained different results for each model, for model 1, QDA, for model 2, SVM and for model 3, decision tree found to gave better results.

A study conducted by Divesh et.al (2022) [60], for prediction of liquefaction potential for different machine learning techniques (extreme gradient boosting (XGBoost), random forest (RF), gradient boosting machines (GBM), support vector regression (SVR), and group method of data handling (GMDH)). The study considers six input variable such as, depth of penetration, corrected standard penetration blow number, total vertical stress, fine content, maximum horizontal acceleration, total effective stress, and earthquake magnitude. Based on R^2 value of testing dataset, XG Boost gave best results, however, SVM is competent.

Table 2 Summary of Literature Review

Application	**Author**	**Objective**	**Algorithms used**	**Evaluation Method**
Slope Stability/Landslide Analysis	Yao et.al (2008) [31]	Landslide Susceptibility Analysis	SVM and Logistic Regression	Accuracy score
	Yilmaz et.al (2010) [32]	Landslide Susceptibility Mapping	Conditional Probability, Logistic Regression, Artificial Neural Networks, and Support Vector Machine	ROC
	Samui et.al (2011) [34]	Slope Stability Analysis	LS-SVM, ANN	R,RMSE, MAE
	Chen et.al (2016) [33]	Landslide Susceptibility Mapping	SVM	ROC
	Li et.al (2014) [36]	Parameter optimization for landslide prediction	GA-SVM	RMSE
	Feizizadeh et.al (2017) [37]	Landslide Susceptibility Mapping	SVM	Accuracy score
	Hong et.al (2017) [38]	Landslide Susceptibility Mapping	SVM	AUC
	Xue et.al (2014) [39]	Slope Stability Prediction	SVM and PSO	Accuracy score
	Zhoa (2021) [41]	Landslide Susceptibility Mapping	SVM and PSO	ROC
	Ballabio et. al (2012) [42]	Landslide Susceptibility Modelling	SVM	ROC
Foundation Analysis	Pal et.al (2008) [43]	Static Pile Capacity Modelling	SVM	R^2
	Samui (2008) [44]	Predicting friction capacity of driven piles	SVM, ANN	R
	Samui (2011) [45]	Bearing Capacity Prediction	SVM	Coefficient of Co-orelation (R)
	Samui (2008) [46]	Prediction of settlement of shallow foundation	SVM	R, MAE, RMSE
	Samui (2012) [47]	Prediciton of Ultimate Bearing Capacity of shallow foundation	SVM and RVM	R, RMSE
	Zhou et.al (2017) [61]	Prediciting safety risks in Deep foundation pits	SVM	R^2
	Li et.al (2019) [49]	Prediction of foundation pit slope displacement	LS-SVM	MAE, MSE

Soil Mechanics	Gill et.al (2006) [50]	Soil Moisture Prediction	SVM and ANN	R, RMSE
	Pal (2006) [51]	Prediction of Liquefaction from SPT and CPT data	SVM	Accuracy score
	Kovacevic et.al (2010) [56]	Prediciton of soil properties and soil type classification	Linear SVM (LSVM), Gaussian SVM (GSVM), Logistic Regression (LR) and Multinomial Naive Bayes (MNB)	R^2
	Das et.al (2012) [57]	Prediciton of field Hydraulic Conductivity	SVM, ANN	RMSE, R
	Besalatpur (2012) [53]	Prediction of Soil Physical Properties	SVM	R
	Kennedy et.al (2015) [58]	Prediction of Soil Organic Carbon	SVM, RF, ANN	RMSE, R^2
	Liu (2016) [54]	Soil Quality Assessment	SVM	Accuracy score
	Samui et.al (2008) [55]	Determination of the Overconsolidation Ratio (OCR)	SVM	RMSE, MAE
	Hanadeh et.al (2022) [59]	Soil Liquefaction Assessment	SVM, Decision Trees, and Quadratic Discrimination Analysis	Accuracy score
	Divesh et.al (2022) [60]	Prediction of Liquefaction Potential	Extreme Gradient Boosting (XGBoost), Random Forest (RF), Gradient Boosting Machines (GBM), Support Vector Regression (SVR), and Group method of Data Handling (GMDH)	R^2

2. Conclusion

The intricate behavior of soil materials presents significant challenges in addressing issues within geotechnical engineering, often complicating the search for optimal solutions and, in some cases, rendering it nearly impossible. A review of the existing literature indicates that Support Vector Machines (SVM) have emerged as a robust machine learning tool extensively utilized for both regression and classification tasks in geotechnical engineering. Due to its inherent simplicity and user-friendliness, SVM has found applications across various domains, including foundation settlement analysis, slope stability assessments, and soil mechanics. Traditional methods, such as the finite element method and limit equilibrium method, predominantly rely on linear models, which can hinder progress in solving complex geotechnical problems. In contrast, SVM has demonstrated exceptional efficacy in addressing both linear and non-linear challenges. Furthermore, when combined with other algorithms, the accuracy of SVM models has been significantly enhanced.

This study thoroughly reviews the application of SVM techniques in the field of geotechnical engineering, underlining its effectiveness in tackling complex problems. SVM serves a critical role as an optimization algorithm, facilitating the classification and prediction of outcomes based on specified parameters.

Compliance with ethical standards

Disclosure of conflict of interest

There is no conflict of interest.

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