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An Assessment for the Predicting of Road Embankment Stability with Artificial Intelligence Techniques

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Abstract

The geotechnical characteristics of soil exhibit uncertain and diverse behavior resulting from complicated and imprecise physical procedures associated with the formation of these materials. Unpredictability modelling of soil behaviour is one of the fundamental difficulties faced by engineers in the design of road embankment stability. Artificial Intelligence (AI) has been increasingly focused on modelling a complicated embankment behavior in studies as it has shown superior predictive capacities compared to conventional methods. The purpose of this paper is to provide a review of certain selected AI methods on their applications in embankment stability and presents key features involved with modelling these AI approaches. This paper subsequently discusses the strengths and constraints of the AI methods chosen in comparison with other approaches to modelling.

Keywords: *Artificial intelligence, Embankment stability, Artificial neural networks and Support vector machine.*

I. INTRODUCTION

The design of road embankment stability is one of the challenging work scopes in geotechnical engineering. The key aspect in the design of road embankment is the settlement, lateral displacements and slope stability as it has considerable influence on safety and structure economic assessment [1]. Due to complex and uncertain soil behaviour, engineers face a challenging task to determine these aspects. This issue has motivated many researchers to use methods of artificial intelligence (AI) to predict and model embankment behaviour.

Recent trends in AI application has led to the proliferation of performed successful studies for almost every geotechnical engineering problem due to their adaptability and high accuracy. AI consists of several branches such as Gene Expression Programming (GEP), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), Artificial Neural Networks (ANNs), Support Vector Machine (SVM) and Flexible Discriminant Analysis (FDA). Recent evidence suggests that AI produces greater efficiency to predict soil behavior than traditional

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statistical models [2].

A number of researchers have reported the performance of ANN and SVM models to predict ground settlement [3], slope properties [4], soil behaviour [5]–[7] and soil erosion [8].

Determining soil characteristics with traditional methods such as experimental to assess embankment stability is a time-consuming and costly procedure. Lack of data in stability analysis based on numerical or analytical methods will affect the design results. More recently, literature has emerged that propose the application of AI to address the problem.

This paper begins with a brief introduction to give an overview of the main characteristics appropriate to the procedures and operations of ANN and SVM. A review of their application to date in the stability of road embankment presented. The challenges and future perspective regarding the application of AI methods in modelling and prediction of embankment behaviour also discussed.

II. OVERVIEW THE THEORY OF ARTIFICIAL INTELLIGENCE

Recently, various new designs in geotechnical engineering have developed the artificial technique of predicting. The ANN, fuzzy logic techniques, support vector machine, and some hybrid techniques are the newly established techniques. Thus, this section provides a brief overview of the ANN and SVM methods.

A. Artificial Neural Networks (ANNs)

A neural network (NN) is a particular paradigm of mathematical computing that models biological neural systems activities. An artificial neural network (ANN) is a method that attempts to replicate the brain functioning and nervous system of humans. A combination of neurobiological and statistical expertise gave rise to a concept that McCulloch and Pitts [9] first proposed in 1943. Since then, with a back-propagation algorithm implemented in 1986 for feed-forward multilayer perceptrons (MLPs), ANN study has evolved quickly [10]. A number of studies have defined ANN's structure and operation [11], [12].

Typically, ANN architecture comprises a number of processing elements. Based on Fig. 1, these elements include one input layer, possibly one or more hidden layers, and one output layer. There are a large number of connections between neurons and capacity to learn from data, providing a robust prediction. Each node can have multiple input connections; however, at their output, only one connection is allowed. The input layer is based on the external world, coming to the ANN as input. The submitted input is subtracted in the hidden layers from each stored vector to predict an output. The hidden layers are input layers that provide information generated from the input layer and are processed for transmitted to the output layer. It is possible to change the number of hidden layers depending on the network structure, but if the number of neurons increased in the hidden layer will increase the complexity and time of calculation. The network structure, however, also allows ANN to be used to solve more complicated issues.

The output layer works to process the information received from the hidden layer to generate the target. A selected mathematical model is utilized to calculate the output part. The normalization process is performed on the output layer by separating outputs from hidden layers that are weighted by values in the summing layer. The back propagation learning algorithms are commonly used in the training process of ANN model development to minimize assumptions as they are very useful and safe.

The error back propagation method was performed with two steps, the first being the phase of the feed-forward in which the output is computed from any node by propagating the input value of the input node. The second step is a backward phase with the use of error criteria to correct the connection weight values.

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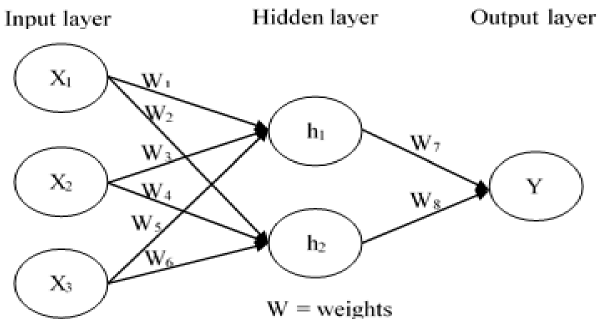

Fig. 1 An ANNs architecture with multi-layered perception (MLP)

In developing the ANN prediction model, nonlinear structures are the essential features for estimation and classification [13]. Methods of learning are essentially split into three groups in the ANN. It is divided into two types of learning control: supervised and unsupervised. The supervised learning with training data serves to train ANN while unsupervised learning is a weights compilation that links mathematical relationships to data without using training kits [14].

Despite the success ANN in geotechnical engineering applications have been achieved, it has some problems such as less generalizing performance, slow convergence speed, arriving at a local minimum and over-fitting problem [15].

B. Support Vector Machine (SVM)

Motivation from statistical learning theory, Vapnik [16] developed SVM to minimize model complexity and prediction error. As a result, it has been proven to be robust and effective based on the regression [17] and classification [16] algorithm. SVM is closely related to ANNs where the SVM model uses the sigmoid kernel function along with two-layer perceptron neural networks. Essentially, the SVM procedure involves a training phase in which the model developed provides a series of sample inputs and target output values. At the end of the training phase, most of the 'learning' models will be used to evaluate a set of test data separated. Besides, the assessment capabilities of the generalized trained model can also be performed with this method.

SVM is based on two primary concepts that are the optimum margin classifier and the use of kernel functions. The optimal margin classifier works to produce a separate hyperplane for maximizing the distance between positive and negative samples while the kernel function is to compute the product from two vector points. The mapping a non-linear kernel allows data to be separated linearly in high dimensional feature space although it cannot be separated in the original input space [16]. For a simple linear classification problem, the SVM concept was first examined and later extended, which included complex tasks involving higher dimensions and nonlinearity. Moreover, the SVM algorithm uses three mathematical principles such as Fermat, Lagrange and Kuhn–Tucker.

The purpose of SVM classification is to set the boundaries of a decision in a feature space that separate different class data points. It is different from other methods because it creates an optimum hyperplane separation between the two classes to minimize generalization error and when two classes are separated, the SVM defines the hyperplane to minimize generalization error, and if both classes are non-separable, SVM attempts to find the hyperplane that maximizes the margins and minimizes the quantities that are proportional to the misclassification error number. Therefore, between the two classes, the chosen hyperplane has the maximum margin. Margin is the sum of the distances between both classes of separated hyperplane or the nearest points [16].

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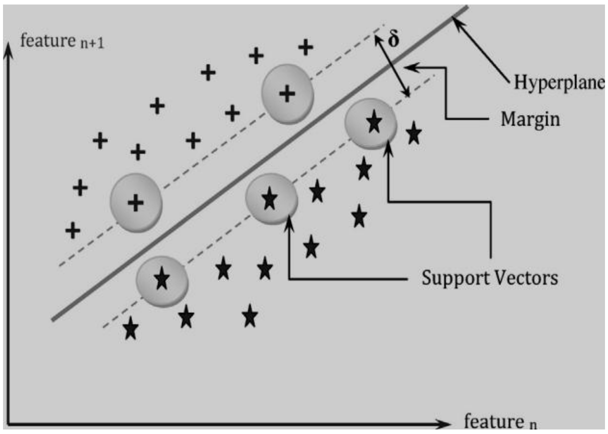

Fig. 2 Hyperplane of maximum separation [18].

There are four fundamental ideas can be understood with SVM classification predictive capabilities such as the segregation hyperplane, kernel function, the soft-margin SVM and the hard-margin SVM [19]. Initially, SVM models were created to classify linearly separable object classes. The two-dimensional plane is shown in Fig. 2 consists of two different classes of (+) and (*), which are linearly separable objects. The purpose is to discover a classifier that completely separates them. The objects framed behind the H1 hyperplane is class (+), while the H2 hyperplane is the class (*) of the object and if the objects fall exactly above the hyperplane of H1 and H2, it is called a support vector.

Determining the exact separation of the hyperplane by dividing the data into real-time problems in space is difficult, and in some cases, it can be obtained from a curved boundary of decision. Based on Fig. 3, among others, the use of SVM is to serve as a classifier for classes that are not separable. In such cases, employing nonlinear functions called feature functions ϕ, it is always possible to map the initial input space to some higher-dimensional function space (Hilbert space) as shown in Fig. 4. Despite the high-dimensional space of the feature, it could not be practically feasible for hyperplane classification to directly use the feature functions ϕ. In these situations, computing can be performed with nonlinear mapping using kernels. Shigeo [20] provides brief more explanations for these SVM classification methods.

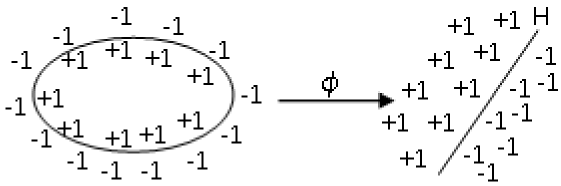

Fig. 3 Linear separation in feature space [18].

The SVM regression concept is based on computing a linear regression function within a high-dimensional feature space where the input information is mapped through a nonlinear function. In other words, the kernel function is used to map input x to high dimensional feature space for support vector regression. It is then modeled linear in this space. Polynomial, linear, radial baseline and sigmoid functions are the most commonly used kernel features. Its uses ε-insensitive loss to perform linear regression in the high-dimensional feature space and at the same moment, attempts to decrease the complexity of the model by minimizing $||w||^2$. The optimization issue can be transformed into a problem of quadratic programming [21]. Schölkopf and Smola [22] have a more detailed overview of the SVM regression.

There are three types of variants in SVM, namely least-squares (LS), linear programming (LP) and *Nu* (v). Suykens et al. [23] proposed least-squares support vector machines (LS-SVM) is a widely applied and functional machine learning technique for both classification and regression. The LS-SVM solution is derived from linear Karush – Kuhn – Tucker equations rather than a traditional SVM quadratic programming problem. Vapnik [16] proposed SVM with fewer support vectors that originally considered a heuristic approach with linear programming support vector machine (LP-SVM). The v-SVM were extracted so that the soft margin is within the range of zero and one, where inhomogeneous separating is performed by SVM using hyperplanes.

The main advantage of SVM is to employ the Structural Risk Minimization (SRM) rather than Empirical Risk Minimization (ERM) as one of the more practical ways to eliminate local minimum issues. Meanwhile, the size of the model selected automatically and based on the principle of structural risk optimization can prevent or reduce over-fit [16].

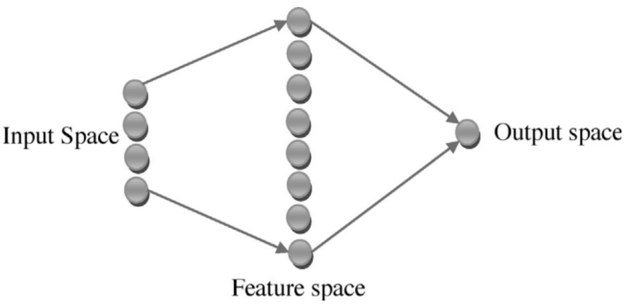

Fig. 4 SVM map in a high-dimensional space [18].

Although many studies have successfully demonstrated that SVM is applied to solve various problems in geotechnical engineering, however, a number of authors have reported certain limitations. The quadratic programming in SVM causes high complexity computations [21]. It is a challenging and complicated task to determine tuning parameter design values, namely the capacity factor, error-insensitive zone, and the kernel parameter [24].

III. ARTIFICIAL INTELLIGENCE APPLICATIONS IN EMBANKMENT STABILITY

This section offers an overview significant of the success of ANN and SVM applications that have emerged in embankment stability studies by comparison or otherwise. Several factors need to be systematically studied in developing AI prediction models for embankment stability problems to improve model performance. These considerations include determining appropriate model inputs, dividing data, preparing data, validating model, robustness of model, transparency of model, extraction of knowledge, and uncertainty of model. Much of the current literature on these factors pay particular attention from researchers. These factors are discussed beyond this paper scope but can be discovered in Shahin [25]. However, in the application presented below, some of these factors are discussed briefly.

A. Ground settlement prediction

The road embankment requires a great safety feature that is controlled by three main criteria, namely, ground settlement, slope stability and lateral displacements of ground. A large and growing literature has predicted the embankment stability constructed on soft ground stabilized with various improvement methods. Several studies that estimate ground settlement have been performed on the embankment with stone columns. Instance, Chik et al. [26] developed a neural network with tenfold cross-validation for the prediction of settlement behaviour of a stone column (SC) under a road embankment. The input parameters for the NN consisted of the internal friction angle, SC spacing, the SC diameter, length of SC, and embankment height while the main output was the settlement. The comparison of settlements measured and predicted for training and testing sets demonstrates that the neural network was capable of modelling the settlement of SC effectively.

The study predictions the embankment stabilized with vertical wick drains had performed Kanayama [27] in 2014. The outcomes of predictions from the ANN models developed were compared to the observed field values. The developed model involves the cubic spline interpolation technique applied to generate additional data between measurements and regulate the for constant time intervals to improve prediction accuracy. Applying this approach, the improved simulations of the network model showed a significant improvement in the accuracy of settlement prediction measurements.

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Yong et al. [28] utilized neural networks to predict the settlement of soft ground in highway using field test data and available data from the literature. The neural network model inputs were the fill height, thickness of treatment, modulus of composite and time while the settlement is an output parameter. The neural network models are developed with a back-propagation to be formalized. The comparison between the predicted and the three traditional methods of hyperbolic methods, the test curve method and the three-point method of ANN model demonstrated that the impressive prediction performance.

Chen et al. [29] have successfully performed prediction of settlement embankment exposed to frozen seasonal with a back propagation neural network approach. The model developed with time and temperature as an input parameter while the output parameter is a settlement. The findings showed that models of neural networks correlate more closely with real measurements.

Aljanabi et al. [30] developed SVM a model for predicting ground settlement embankment stabilized with stone columns. The proposed model of SVM and SVR was compared with the existing reference settlement prediction model using monitored field data and subsequently validated their achievements. As a consequence, by using the *v*-SVM regression associate with tenfold cross-validation, a better prediction accuracy could be accomplished.

More recently, Kirts et al. [31] suggested an SVM model predict road embankment on soft ground and to test the efficiency of these correlations in terms of settlement computation through field verification. Predictions of the settlement were produced for each soil layer based on the predicted and measured recompression index. Applying the recompression index correlations and the compression index can provide a reasonable prediction of the settlement, and the predicted recompression index reveals that the settlement prediction is robust. The results show that the settlement of predicted is lower than the measured.

B. Slope stability of embankment

As previously mentioned, a reasonable estimate of the slope stability is required for road embankment design. The relationships between factors affecting slope embankment are complicated, multi-factorial, and often mathematically tricky to define, posing a challenge to predict slope stability. The approach to problem estimating the stability of the slope with the AI methods is complicated task and requires sophisticated modelling techniques, in-depth engineering knowledge, experience and a large number of experimental data. Due to the difficulty and complexity faced to determine the input data such as soil parameters, accurate estimation of slope stability is a challenging issue. For this reason, the values of vital input data are difficult to determine.

Sakellariou and Ferentinou [32] developed ANN models to predict slope safety factors by using parameters that affect slope stability as input variables. Several sets of threshold logic unit networks have been tested with adjustable weights, and back propagation algorithms were used for calculations in the training process. Six factors that influence the stability of slope are considered to be potential variables of the input model, including soil friction angle, cohesion, soil unit weight, slope angle, slope height and pore water pressure. The network performance is evaluated, and the results are compared utilizing conventional analytical techniques. Better convergence was achieved between the safety factor estimated from neural networks and calculated from analytical techniques compared to the results from the least square approximation technique from analytical techniques.

The complexity of estimating slope instability in traditional techniques that have large freedom degrees and their behavior is vulnerable to the

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conditions the need for an effective new technique to predict the non-linear feature of landslides. For this reason, Wang et al. [33] utilized Back Propagation Neural Networks (BPNN) to evaluate instability of slope with 5-2-2-2 BPNN architecture were built using a collection of training landslide samples across the Qing River region. In this study, input parameters are bulk density, slope height, slope angle, cohesion and internal friction angle while slope stability and the safety factor is an output parameter. This study attempts to evaluate slope instability utilizing the BPNN model in conjunction with a comprehensive analysis of soil microstructure and field survey along the sliding surface using the Scanning Electron Microscope (SEM). The predicted findings from this study revealed that the safety factor was 1.10, indicating that the landslide of a case study is presented in a marginally stable condition.

Motivation from the advantages of ANN methods capable of modelling highly complicated and non-linear functions, Choobbasti et al. [34] have developed model slope stability predicts in specific locations, based on-site investigation data available from Noabad, Mazandaran, Iran. The ANN is modelled with a multilayer perceptron networks were consisting of six essential parameters as input parameters, i.e. angle of slope, effective stress, total stress, friction angle, cohesion, and horizontal earthquake coefficient, while slope stability is output parameter. The algorithm of back propagation is utilized in the training process so that the network reaches the error function less than the desired tolerance. The results are compared to the classic limit equilibrium methods for checking the validity of the ANN model. This study reveals that the outcomes of ANN were considered close to the value calculated by the classical technique of Bishop.

The need for a tool that can assist predict a slope stability state has been recognized for a long time, and a number of best practice guidelines have been published. As an improved approach, Lu and Rosenbaum [35] utilize the combination of ANN and Grey Systems to predict likely slope stability conditions. ANN techniques are ideal for quantities of essential data available while the Gray System is particularly useful where the explicit mechanisms responsible for the landslide are unclear, but relevant information and limited data are available. The results of these techniques have proven that the tools developed are able to analyse and predict future soil movements based on geotechnical features and historical behaviour.

There are some limitations due to the generalization ability of the conventional ANN, Samui [36] developed the SVM model to predict safety factors as a issue of regression and stabilization that was modelled as a issue of classification. This study utilizes spline, radial basis function and polynomial function as SVM kernel functions while the ε-insensitive loss function is used in the analysis process. Using the data collected by Sakellariou and Ferentinou [32], the data is divided into two sub-sets, training datasets and test datasets for model development and estimate model performance. As a consequence of evaluating the slope stability prediction performance model, the SVM model yields better outcomes than the earlier published ANN model.

On the other hand, Samui and Kothari [37] used least-square vector support (LSSVM) to predict safety factors of a slope using six input parameters consisting of cohesion, pore water pressure, slope height, soil unit weight, friction angle and slope angle. This study applies six input parameters consisting of the cohesion, pore water pressure, slope height, soil unit weight, friction angle and slope angle. The developed LSSVM and ANN performed a comparative study. This study demonstrates that the LSSVM developed for slope stability analysis is a robust model.

Due to the propose from other researchers that slope stability analysis was performed with a hybrid approach, Li et al. [38] using the LSSVM algorithm based on quantum-behaved particle swarm

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optimization (QPSO) to establish nonlinear stability of the slope. This study compares the QPSO-LSSVM algorithm with PSO-LSSVM and LSSVM algorithms using training and testing samples of slope stability analysis. The results show that QPSO-LSSVM is considered the best suited for this work because it has the best convergence performance and fast search velocity compared to the other three algorithms.

In order to estimate the slope stability, the approach with a hybrid model can also address engineering problems involving multiple parameters. This reason encourages Xue et al. [39] to develop hybrid models by combining methods of SVM and particle swarm optimization (PSO) to improve the performance of slope stability prediction. Several significant parameters were used as input parameters, including unit weight, friction angle, cohesion, pore water pressure coefficient, slope angle and slope height, while slope status was the output parameter. The results reveals that PSO-SVM is a powerful computing tool which can be employed to predict the stability of the slope.

In other work, Xue [40] provided two examples of slope stability cases to validate slope stability prediction performance by using a modified PSO algorithm to select the optimal value of the LSSVM parameter. The PSO-LSSVM model proposed in this study found that its prediction performance showed good agreement with high accuracy.

C. Lateral displacement of ground embankment

The lateral displacement are one of the three criteria governing embankment stability design as a ground movement should be checked to ensure that certain boundaries are not exceeded. However, lateral displacements of the ground embankment is less critical than settlement and slope stability; therefore, less attention from AI researchers.

In the last two decades, Wang and Rahman [41] developed the BPNN model to predict lateral ground displacements. In their study, they used a feed-forward network with Levenberg-Marquardt algorithm for training stages. The findings of this study reveal that the BPNN model acts as a simple and reliable predictive tool for the total of horizontal displacement of the ground.

Baziar and Ghorbani [42] modelled BPNN with seven input parameters and one node on the hidden layer to predict the horizontal ground displacement on the slope of the ground. Input parameters in the study are an earthquake magnitude, the saturated granular thickness, distance from the energy source to the site, the average mean grain size, the average fines content, ground slope and free-face ratio. The root means square errors and correlation factors in this model demonstrate the neural network approach's superiority over traditional regression analysis.

Due to its the convenience and cost-effectiveness of traditional methods, Chiru-Danzer et al. [43] developed BPNN based on field data to predict the horizontal displacement of liquefaction-induced. The database for ANN modelling and analysis is a database consisting of 443 measurements of horizontal displacements. It turns out that the results of the study found the ANN model yielded a predictive ability than traditional methods.

In the past decade, Oommen and Baise [44] utilized Support Vector Regression (SVR) to develop lateral displacements-spreading modeling by setting the framework for validation of existing models and developing SVR model in comparison to existing Multilinear Regression (MLR) model. The results are found that SVR has a better random capability than the commonly used empirical relationships using MLR. In addition, SVR model analysis and its support vectors help identify data gaps and define the scope for future data collection.

Due to it is challenging to evaluate the mechanism of lateral flow quantitatively, Lee and Kim [45] developed an SVM model to predict lateral flow occurrences based on measured field data and compared with conventional empirical method

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results. A total of 101 case studies were used for evaluation, and the database was divided into three categories, namely A, B and C. The research findings found that the proposed model of recognition of SVM patterns can predict the occurrence of lateral flow more appropriately and practically than conventional empirical methods.

Recently, Aljanabi et al. [30] used *v*-SVM to predict the displacement of the soft ground under road embankment with the SC. The number of the stone column prediction inaccurate lateral bulging decreased significantly with the SVM technique. The results of their studies found that the SVM model can predict lateral bulging of the SC with a relatively good accuracy, where errors for most records did not reach 16%.

IV. DISCUSSION AND CONCLUSIONS

In the road embankment construction, the physical and engineering properties of ground have varying and uncertain behaviours, which makes it difficult to understand well. In order to address these problems and complexity, AI as an alternative approach can provide some advantages over more traditional computing techniques. Lack of physical understanding with some assumptions made into the model is a significant problem in traditional techniques. Besides, models derived from traditional methods may not be optimal as they depend on the assumptions of the model structure. As a result, many traditional methods model fail to simulate the complex behavior in the road and geotechnical engineering problems. Instead, the AI method is a strategy for development-driven based on input and output of data training to determine structural of parameters and models. As a result, there is little need for moderation in this issue or the integration of these assumptions. Furthermore, predictive models with AI methods are updated continuously as new data is available to improve results by presenting new training examples. Thus, these factors make the AI method as a robust predictive modelling tool in the road embankment engineering.

In reviewing the literature, it is clear that the AI technique has been successfully applied to the road embankment stability behaviour, including ground settlement, slope stability, lateral displacements of ground. However, the application is most focused on the prediction of slope stability and the estimated ground settlement, while the estimated lateral displacement of the ground is less attention. In this regard, it can be ascribed to the actual that in the design of road embankment stability, the lateral displacement is less important. In most reviewed applications of AI in road embankment stability, a convenient formulation suitable for manual calculation was possible provided to the relationship between the input model and the corresponding output. It can assist and facilitate the development of AI model and making it easily accessible to users. Based on the findings of the application study review, it can be concluded that the AI technique has a better performance than the traditional method. However, the development of a predictive model of embankment stability with the SVM approach is very little was found in the literature. The most interesting finding was that SVM techniques could overcome the limitations found in ANN techniques such as arriving at a local minimum, slow convergence speed and over fitting problem.

Despite the AI technique has been adapted successfully, it still faces classic problems as several limitations need to be addressed in the future include model uncertainty, lack of transparency, and knowledge extraction. Particular attention should be given, for instance, to incorporating the previous knowledge of the underlying physical process in the learning formulation based on human expertise. Improvements in these problems will significantly enhance the utility of AI methods and provide the best way for improving the field to the next level of application and sophistication for the next generation of applied AI models.

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