Hybrid artificial intelligence approach based on metaheuristic and machine learning for slope stability assessment: A multinational data analysis

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ABSTRACT

Slope stability assessment is a critical research area in civil engineering. Disastrous consequences of slope collapse necessitate better tools for predicting their occurrences. This research proposes a hybrid Artificial Intelligence (AI) for slope stability assessment based on metaheuristic and machine learning. The contribution of this study to the body of knowledge is multifold. First, advantages of the Firefly Algorithm (FA) and the Least Squares Support Vector Classification (LS-SVC) are combined to establish an integrated slope prediction model. Second, an inner cross-validation with the operating characteristic curve computation is embedded in the training process to reliably construct the machine learning model. Third, the FA, an effective and easily implemented metaheuristic, is employed to optimize the model construction process by appropriately selecting the LS-SVM's hyper-parameters. Finally, a dataset that contains 168 real cases of slope evaluation, recorded in various countries, is used to establish and confirm the proposed hybrid approach. Experimental results demonstrate that the new hybrid AI model has achieved roughly 4% improvement in classification accuracy compared with other benchmark methods.

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1. Introduction

In many countries, due to the population expansion and economic development, extensive road networks and residential areas have been constructed in the hilly or mountainous regions. This leads to the fact that many man-made facilities are susceptible to damages caused by slope collapses. Slope collapses are complex natural hazards that bring about disastrous consequences (Lu & Rosenbaum, 2003). Such hazards are responsible for heavy destructions of public/private property, disruptions of traffic, and losses of human lives every year (Cheng & Hoang, 2015b; Kang & Li, 2015; Tien Bui, Pradhan, Lofman, Revhaug, & Dick, 2013).

Hence, to prevent and mitigate the damages, slope stability analyses are required and better tools for slope assessment are of practical need in the field of civil engineering. The analysis results can be used for identifying collapse-prone areas. Based on such information, Government agency can acquired better knowledge about slope occurrences and the task of allocating financial resources to construct the retaining structures and establishing evacuation plans can be performed more efficiently (Cheng & Hoang, 2015a; Ghosh, Bhattacharya, Boccardo, & Samadhiya, 2015).

In effect, the slope failure prediction can be formulated as a pattern recognition task (Zhao, Yin, & Ru, 2012). To establish a slope assessment model, historical cases of slope failures in the studied areas are first recorded; accordingly, certain features that characterize the natural conditions of the areas are extracted for analysis (Wang, Xu, & Xu, 2005). Based on the collected database, a machine learning method can be employed to generalize the decision boundary that separates the input features of an earth slope into two distinctive classes: 'stable' and 'unstable'.

Proposed by Suykens, Gestel, Brabanter, Moor, & Vandewalle, 2002, the Least Squares Support Vector Classification (LS-SVC) is an advanced machine learning method which possesses many advanced features reflected in its prediction accuracy and fast computation. During the LS-SVC training process, a least squares cost function is proposed to obtain a linear set of equations in the dual space. Accordingly, it is only required to solve a set of linear equations to derive the model structure. Although successful applications of the LS-SVC have been reported in a wide span of problem domains (Ghosh, Guha, & Bhar, 2013; Liu & Zhou, 2015; Samui & Kothari, 2011), a few studies have investigated and harnessed the capacity of this AI approach in slope failure prediction.

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Due to the complex and multi-factorial interactions among factors that affect slope stability, the task of slope assessment remains a significant challenge for civil engineers. Thus, this research proposes an AI framework based on the LS-SVC to establish a novel slope assessment model. The LS-SVC is utilized as a pattern recognition technique to classify slope conditions into two classes: 'stable' and 'unstable'. Furthermore, to better determine the LS-SVC's hyper-parameters and reliably construct the prediction model, the Firefly Algorithm (FA) (Fister, Fister Jr, Yang, & Brest, 2013; Hassanzadeh & Kanan, 2014) and an inner cross-validation with computation of the area under the operating characteristic curve are employed. The remaining part of this paper is organized as follows. The second and third sections of this paper present the literature review and the research methodology. The framework of the proposed model is described in the next section. The fifth section reports the experimental results. Conclusions of this study are stated in the final section.

2. Literature review

Due to the criticality of slope stability assessment, various research works have been dedicated in tackling this problem of interest. Currently, expert assessment, analytical methods, and machine learning are commonly employed for analyzing slope conditions. The first method is based on experts' experiences and knowledge (Cheng & Hoang, 2014). Using experts' judgments, the possible factors that trigger slope collapses can be identified and the condition of a slope can be evaluated. However, the major disadvantage of the expert assessment approach is that it strongly relies on subjective judgments and it is infeasible to ensure the consistency of the prediction outcomes.

The analytical methods are derived from the slope displacement models; based on this approach, one can analyze the slope stability by identifying of the most dangerous sliding surface and calculating the factor of safety (Baker, 2003; Kostić, Vasović, & Sunarić, 2015; Li & Chu, 2015; Salmi & Hosseinzadeh, 2015). The analytical methods require input parameters for every calculation point of the studied region; this brings about serious problems in data collection as well as in controlling the spatial variability of the input parameters. Therefore, the analytical methods are only appropriate for evaluating slope stability in small regions (Song et al., 2012).

Recently, machine learning has been proved to be a feasible and effective approach for slope assessment. In general, machine learning models are established based on artificial intelligence (AI) techniques and historical databases (Cheng & Hoang, 2015b; Esmaeili, Osanloo, Rashidinejad, Aghajani Bazzazi, & Taji, 2014). Using these models, the slope stability evaluation can be formulated as a classification problem in which prediction outputs are either "stable" or "unstable". By learning events of slope collapse in the past, machine learning approaches can produce predictive results for unlabeled patterns.

Thus, applying machine learning approaches for solving the task at hand has been an attractive research theme. Yan and Li, (2011) constructed a method for predicting the stability of open pit slope based on the Bayes Discriminant Analysis (BDA). A hybrid instance-based classifier relied on the Fuzzy K-Nearest Neighbor was established for slope stability assessment (Cheng & Hoang, 2015a). Wu, Kung, Chen, and Kuo, (2014) proposed a model for predicting and monitoring slope disaster by employing the K-means model to derive the weight and classification of disaster factors. Cheng and Hoang, (2014) evaluated slope collapses across mountain roads with the employment of the Bayes theorem.

Lu and Rosenbaum, (2003); Zhou and Chen, (2009); Jiang, (2011); Das, Biswal, Sivakugan, and Das, (2011), and Wang et al., (2005) applied the Artificial Neural Network (ANN) to predict the slope stability. The Evolutionary Polynomial Regression (Ahangar-Asr, Faramarzi, & Javadi, 2010) and the Least Squares Support Vector Machine (Samui & Kothari, 2011) have been used to model the mapping function between the input pattern and the factor of safety of slopes against failure. Zhao et al., 2012 utilized the Relevance Vector Machine (RVM) to explore the nonlinear relationship between slope stability and its influence factors.

Forecasting models of slope stability based on the Support Vector Machine (SVM) were developed by Li and Wang, (2010); Li and Dong, (2012); Cheng, Roy, and Chen, (2012), and Cheng and Hoang, (2015b); these studies found that SVM forecasting models has more advantages to slope stability evaluation over ANN model under the condition of limited data.

Previous researches have demonstrated that that machine learning can provide a viable tool to establish a structured representation of the slope system, which allows the prediction of the slope stability. This study aims at extending the body of knowledge by investigating the capability of the LS-SVC in solving the task of interest. In order to construct and confirm the prediction method, a dataset including real cases of slope evaluation has been collected from the literature. In addition, the training process of the LS-SVC is enhanced by utilizing the FA optimization and an embedded cross-validation used for model evaluation.

3. Research method and material

3.1. Least Squares Support Vector Classification (LS-SVC)

This section describes the formulation of the LS-SVC for solving classification problems. In the historical data, given a training dataset $\{x_k, y_k\}_{k=1}^N$ with input data $x_k \in R^n$ where N is the number of training data points, n denotes the data dimension, and the corresponding class labels is defined as $y_k \in \{-1, +1\}$ the LS-SVC formulation for classification is presented as follows (Suykens et al., 2002):

$$\text{Minimize } J_p(w, e) = \frac{1}{2}w^T w + \gamma \frac{1}{2}\sum_{k=1}^N e_k^2 \tag{1}$$

$$\text{Subjected to } y_k\left(w^T \phi(x_k) + b\right) = 1 - e_k, k = 1, \ldots, N \tag{2}$$

where $w \in R^n$ is the normal vector to the classification hyperplane and $b \in R$ is the bias; $e_k \in R$ are error variables; $\gamma > 0$ denotes a regularization constant.

The Lagrangian is given by:

$$L(w, b, e, a) = J_p(w, e) - \sum_{k=1}^N \alpha_k\left\{y_k\left(w^T \phi(x_k) + b\right) - 1 + e_k\right\} \tag{3}$$

where α_k are Lagrange multipliers; $\phi(x_k)$ represents a kernel function. The conditions of optimality can be stated as follows:

$$\begin{cases} \frac{\partial L}{\partial w} = 0 \rightarrow w = \sum_{k=1}^N \alpha_k y_k \phi(x_k) \\ \frac{\partial L}{\partial b} = 0 \rightarrow \sum_{k=1}^N \alpha_k y_k = 0 \\ \frac{\partial L}{\partial e_k} = 0 \rightarrow \alpha_k = \gamma \, e_k, k = 1, \ldots, N \\ \frac{\partial L}{\partial \alpha_k} = 0 \rightarrow y_k(w^T \phi(x_k) + b) - 1 + e_k = 0, k = 1, \ldots, N \end{cases} \tag{4}$$

The linear system below is obtained after the elimination of e and w:

$$\begin{bmatrix} 0 & y^T \\ y & \omega + \gamma^{-1}I \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ 1_v \end{bmatrix} \tag{5}$$

which $y = y_1, \ldots, y_N$, $1_v = [1; \ldots; 1]$, and $\alpha = [\alpha_1; \ldots; \alpha_N]$. And the kernel function is applied as follows:

$$\omega = y_i y_j \phi(x_k)^T \phi(x_1) = y_i y_j K(x_k, x_1) \tag{6}$$