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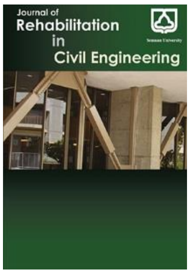

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Intelligent Classification of Stable and Unstable Slope Conditions Based on Landslide Movement

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ABSTRACT

One of the most critical problems in the study of geohazards is the displacement brought on by landslides. This research aims to investigate stable and unstable conditions for this important issue using new techniques. There are several effective parameters on landslide movement that need to be thoroughly investigated/observed, making the process of determining the movement of landslides a difficult one. In this research, different machine learning-based approaches were used to analyze and manage this problem. A set of data was compiled for this investigation including groundwater level, prior rainfall, infiltration coefficient, shear strength, and monitored slope gradient are all influential in landslide movement. Three models of Tree, Adaboost and artificial neural network (ANN) were developed for classification into two categories, stable and unstable. The results showed well that two Adaboost and Tree models can provide significant performance for determining stable and unstable conditions. For the test data, the Adaboost model with an accuracy of 0.857 has the highest accuracy, followed by the Tree model with an accuracy of 0.786. Finally, in this research, unstable data using machine learning was used to evaluate and predict the amount of slope movement. This system is well suited for its high flexibility and high-accuracy assessment for conditions with more movement.

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1. Introduction

One of the fundamental concerns of landslide studies is the phenomenon of ground movement. The dangers to both infrastructure and people can be mitigated by prevention and control efforts [1–4]. However, due to the many factors that might influence a landslide, the occurrence of one is not always anticipated. Several researchers, like Crosta and Agliardi [5], have found that geological and climatic circumstances are major factors in landslide occurrence. As a result of research into the mechanism that controls landslides, a number of models for evaluating the severity of these events have been established [2,5–9]. Many of these research fall into one of four broad types, including statistical models, numerical simulations, physical simulations, and nonlinear simulations [10]. Non-linear models can provide superior performance than alternative methods since the landslide phenomenon is multifaceted, and the interconnections between its many components are quite intricate. Complicated problems can be predicted with the use of non-linear and simulation techniques, which will introduce an indirect assessment [11].

Some of the more cutting-edge technologies recently implemented in the scientific and technological communities include artificial intelligence (AI) methodologies [12–18]. In engineering, these smart computational methods can offer several models, then use those models to present relevant links and predictions [19]. Artificial intelligence (AI) methods have been used and suggested in civil engineering for a wide range of prediction and optimization tasks [20–24]. Classification and regression tree (CART), artificial neural network (ANN), support vector regression (SVR), and generalized linear (GENLIN) model are all popular methods in these fields [25–34]. There have been a number of well-thought-out studies recommended to address landslide issues [3,6,10,35]. Predictive model accuracy can be improved through the creation of ANNs [36]. However, the efficiency of certain computations can be impacted by the use of various AI-based model types. Gene expression programming (GEP) is one such novel approach, and it has proven itself to be quite effective at solving issues in the engineering sciences [37]. This approach, which is a hybrid of a genetic algorithm (GA) and a genetic programming (GP), can present/provide a mathematical equation for prediction while also solving complex problems and improving the accuracy of predictive models [38]. Particularly, many classification issues [39,40] are being solved with the help of artificial intelligence techniques as decision trees, support vector machines, Naive Bayes classifiers, etc., because of their many benefits. The use of AI in soil classification has seen only a small number of recent investigations [41–43]. These investigations demonstrated that AI has the potential to be an effective method for classification of geotechnics problems. Classification of stable and unstable state of landslides according to different conditions is always an important issue in civil and mining projects [44–46]. Considering the risks and costs that this issue creates for the environment and various projects, investigating new solutions using AI models is effective.

Ultimately, the objective of this research is to formulate multiple intelligent models, encompassing Tree, Adaboost, and artificial neural network (ANN) models, to investigate the stability conditions of landslides. The influential factors affecting ground movement were investigated, and diverse datasets were collected for the purpose of model development. This research comprises several distinct phases. Initially, the utilized data is scrutinized and presented in a statistical manner. Subsequently, the complete simulation process of the three models is executed and applied, and their efficacy in predicting and categorizing samples is assessed. Finally, a comparative analysis is conducted encompassing performance metrics, simulation procedures, and various constraints.

2. Methodology

2.1. Data collection

Different kinds of information that Neaupane and Achet [47] utilized to determine the path of landslides were compiled for this investigation. Groundwater level (m), prior rainfall (mm), infiltration coefficient (f), shear strength (kN/m^2), and monitored slope gradient (degrees) are all influential in landslide/slope movement. These values were chosen after careful consideration of the results of prior studies [35,47]. Prediction networks were trained and tested with these data, and the values of landslide movements were analyzed and forecasted as a result. Table 1 presents a statistical breakdown of the information used in the modeling procedure. The next few paragraphs will detail how this information will be used to construct various models for predicting landslide progress. Figures 1-6 show several data distributions statistically. As can be seen, the input parameters to intelligent models have different values, which shows that the models analyze different ranges of data, and their prediction and classification can be justified using nonlinear and multivariate models. Moreover, for different researches, it is possible to consider the ranges of the data used to develop the models in this research for different models. The original study [47] contains more information about the data collection and study location.

Table 1. The data distribution.

Parameter	Unite	Min	Average	Max
Shear strength	KN/m^2	53.97	59.65	60.42
Antecedent rainfall	mm	0	401.96	720
Groundwater surface	mm	-17.5	-10.77	-4.4
Slope gradient	degree	24.8	24.95	25.1
Infiltration coefficient	-	0	28.57	2.03
Slope movement	cm	0	0.82	4.3

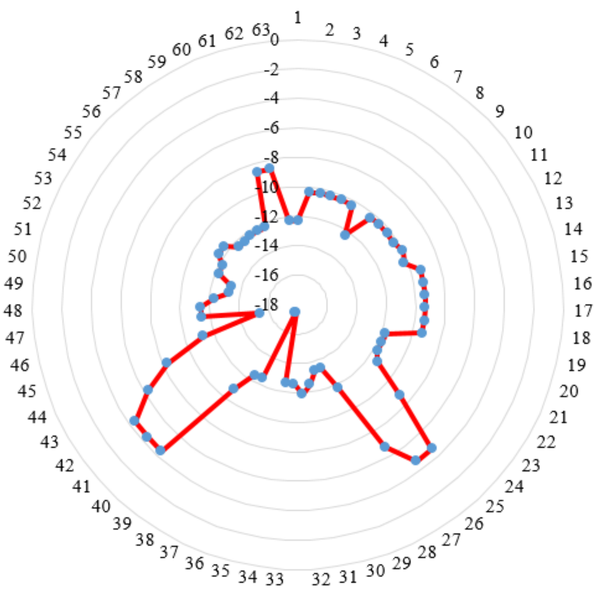

Fig. 1. The data distribution of Groundwater surface.

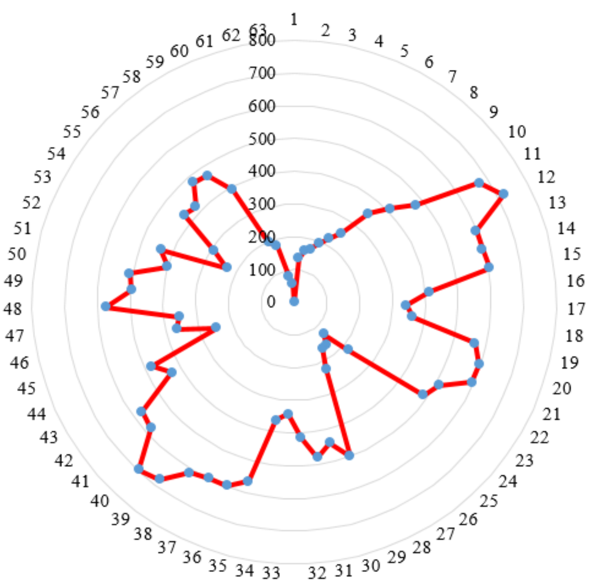

Fig. 2. The data distribution of antecedent rainfall.

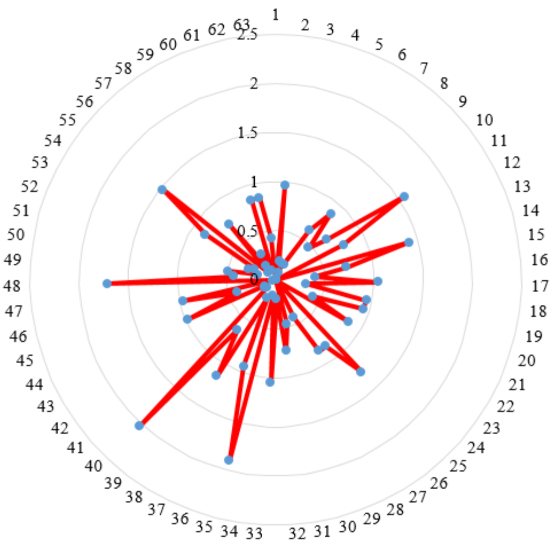

Fig. 3. The data distribution of infiltration coefficient.

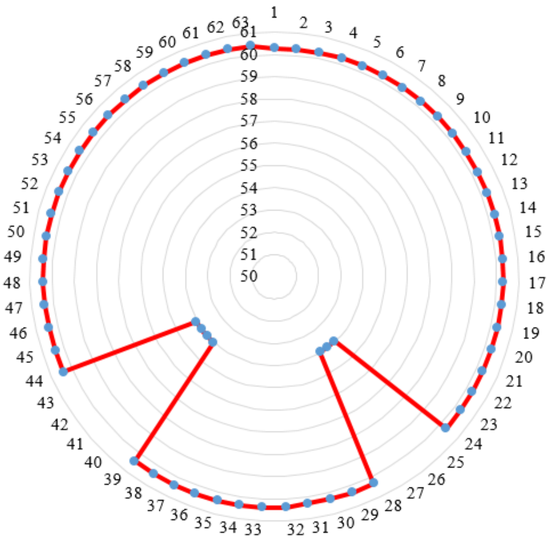

Fig. 4. The data distribution of shear strength.

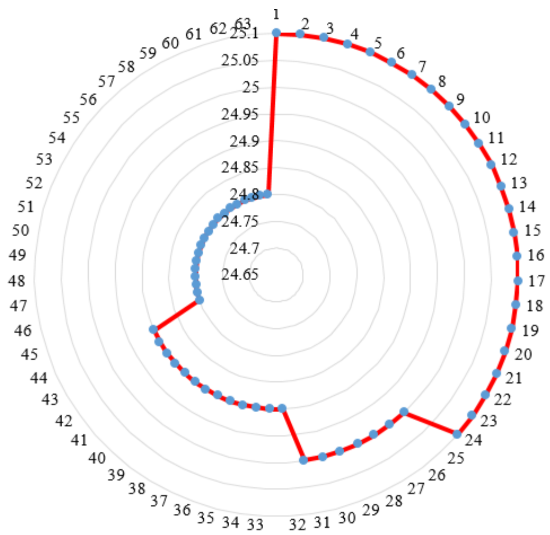

Fig. 5. The data distribution of slope gradient.

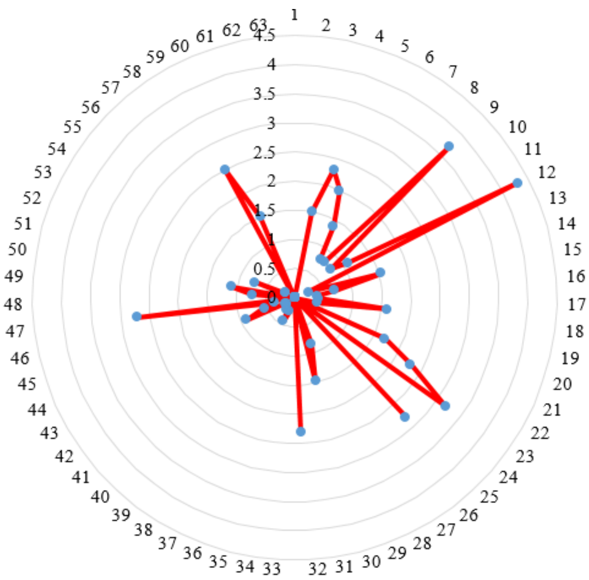

Fig. 6. The data distribution of slope movement.

3. Modeling process

In this part, simulations are used to determine the classification of the landslide to two stable or without movement (Class 1) and unstable or with movement (Class 2) conditions. Various data sets were examined before the modeling process began. The dataset requires preliminary examination due to the presence of two types of class with varying distributions. The first stage involved splitting the data into two halves for training and testing purposes using two distinct distributions. Recent studies also found that a larger percentage of data (80%) was devoted to the training phase for model design. The remaining information was placed into the modeling section but was not utilized during the design phase. The overview of the procedure used in this research is illustrated in Figure 7.

3.1. Tree modeling

The tree algorithm is a hierarchical algorithm that can be applied to different ranges of data. This technique constructs a goal-specific prediction and evaluation model by partitioning the independent data [48–50]. Classification and regression are just two of the many applications of the tree method.

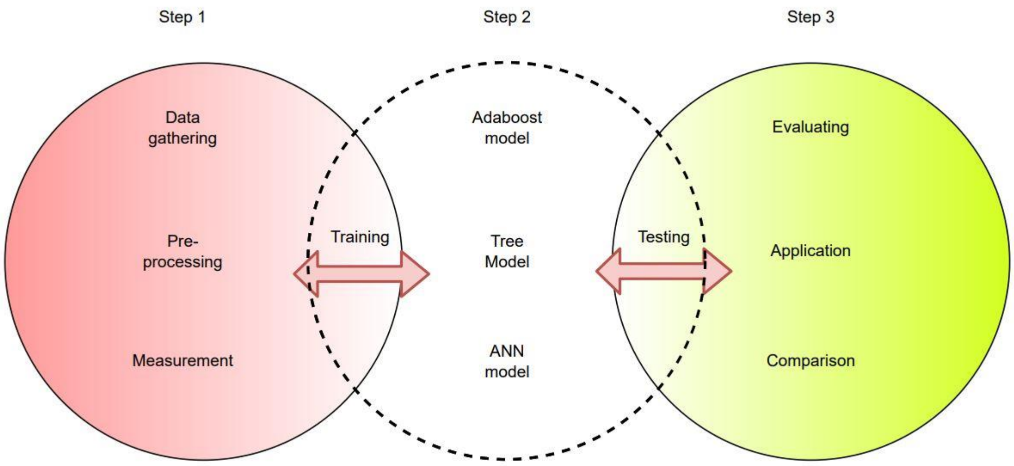

Fig. 7. Research general view.

Tree-based models excel in part because of their ability to identify various associations between variables [51]. These models are flexible enough to function with a wide range of assumptions and data structures. Tree models are convenient since they are simple to build and yield accurate results. Yet, taming the noisy data is preferable for enhanced performance.

Figure 8 illustrates the overarching structure of the tree algorithm. In essence, the method comprises a central root node and several subsidiary branches (internal sections). The internal components may alter in shape and size due to factors such as learning, data dispersion, and data volume. Notably, the leaves are connected to these internal elements. Over the course of time, a tree structure takes form, within which various computations are carried out.

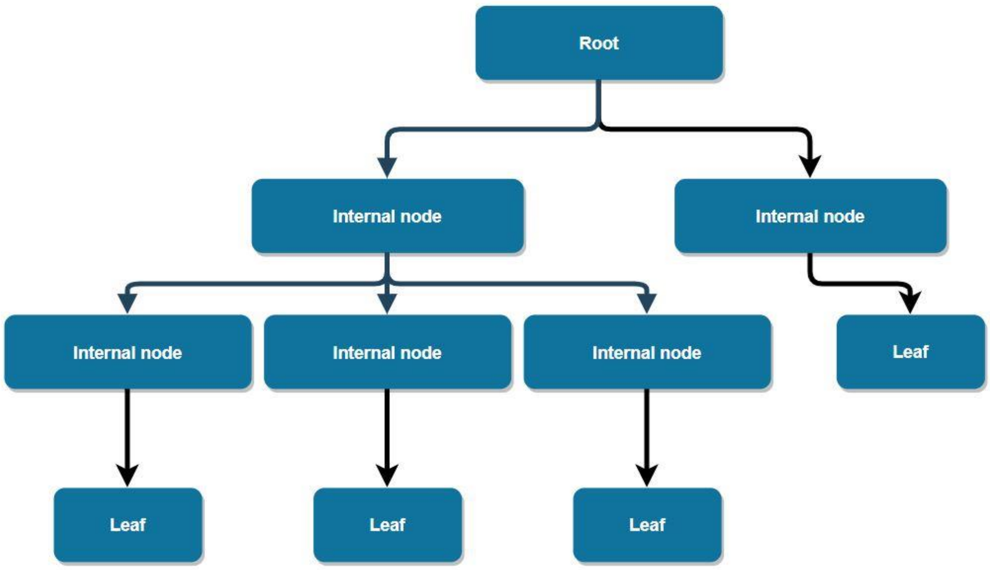

Fig. 8. Tree method structure.

Landslide classification in this study was achieved using a tree algorithm. During the training of the tree algorithm, 80 percent of the data was utilized. This subset included the two classes, 1 and 2, which were deemed most crucial for distinguishing stable and unstable conditions. This algorithm was fine-tuned by adjusting a number of its influencing factors in order to boost the classification performance of the underlying model. Since the tree technique is hierarchical in nature, the parameters are broken down into sub-branches that correspond to their frequency of occurrence, allowing for precise categorization by parameter type. To account for this, we split the minimum for each leaf into two parts. This will reduce the size of the tree's outline and spare extra computing resources. It is important to remember that the variation in inputs and data distribution accounted for these shifts. For this case, the number 5 serves as the dividing line between the several internal sub-sections. The algorithm can then better understand how to proceed with the splitting process as a result. Last but not least, the tree depth is a crucial variable. Parametric studies were conducted on depths between 2 and 12 to identify the optimal conditions. The best depths that were reached were 3, at most. Ultimately, a model optimal for identifying landslide type categorization utilizing a tree algorithm was presented.

The complete structure of the tree results is presented in Figures 9 and 10 for classes 1 and 2, respectively. As evident from these figures, the tree algorithm allows for the assessment and extraction of the significance of each parameter, along with the likelihood of predicting each section based on the associated branches. These results, which are presented separately for classes 1 and 2, can be presented in different ways, which are discussed below.

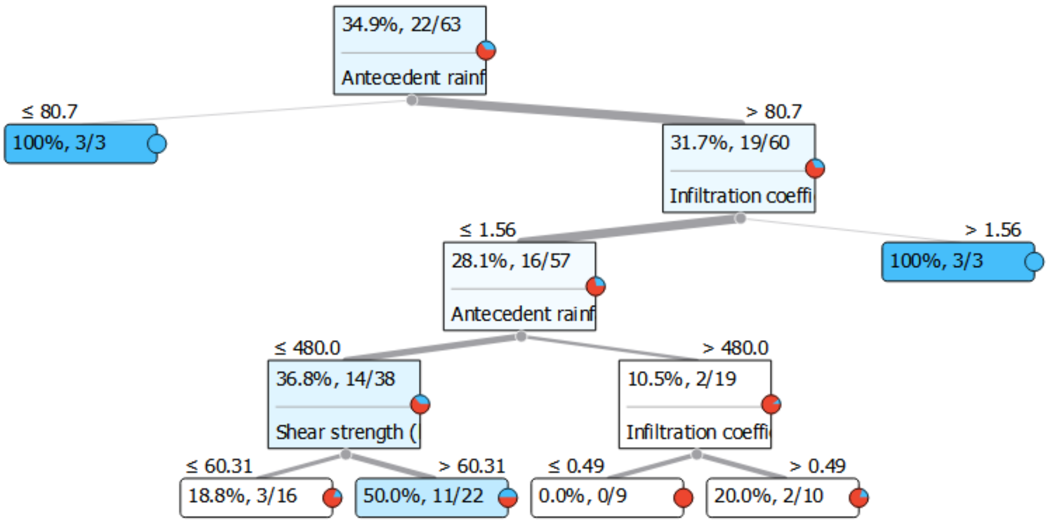

Fig. 9. The tree structure for class 1.

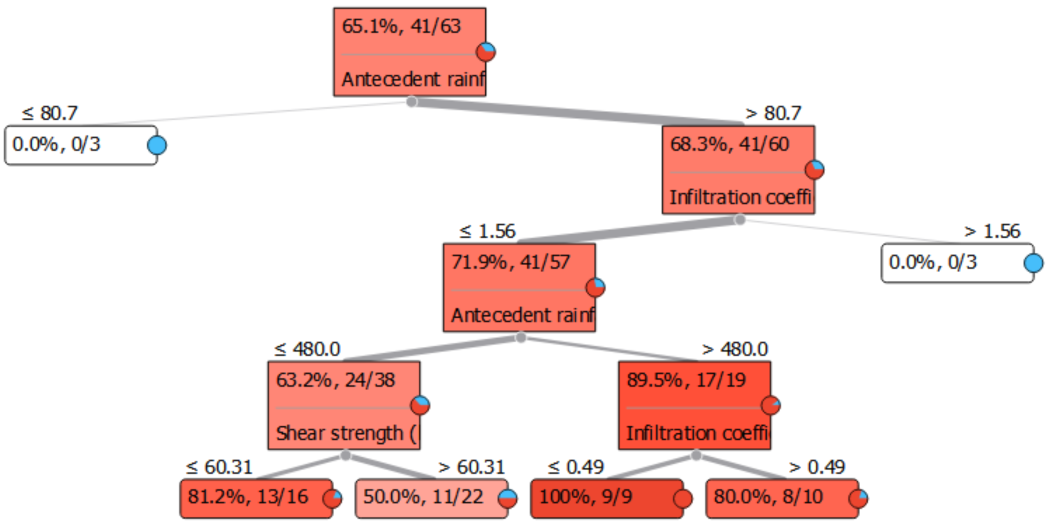

Fig. 10. The tree structure for class 2.

The abilities of the constructed models were assessed using the confusion matrix, which was also utilized during both their training and testing stages. The outputs of the models are sequentially depicted in Figures 11 and 12. For the training part, 76.5% of the data are successfully classified for class 1 and for class 2 this percentage is 75.0%. While for the test section, the percentage of successful classification for class 1 has reached 80% and for class 2 has increased to 77.8%. Last but not least, this creation of these two forms is promising for identifying landslide conditions.

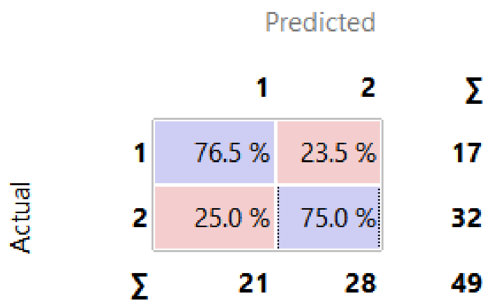

Fig. 11. The training section of tree confusion matrix.

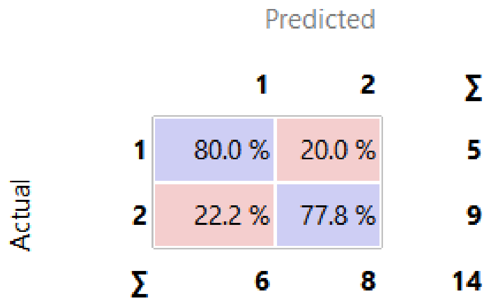

Fig. 12. The testing section of tree confusion matrix.

3.2. AdaBoost modeling

Freund [52] presented the world with the powerful Adaboost algorithm, which is used in machine learning. In order to provide a more robust set of models, this approach is initially refined using only the weak classifiers. As with the tree technique, this one, too, can be utilized to deal with classification and regression issues [53]. Figure 13 depicts a sample use of this technique to show how it works. This is a great example of how to use many classifications to arrive at a final model.

This research employed the tree algorithm as a subpar classifier within an adaboost framework. Being a tree-based model, the optimal tree model was chosen in the previous stage. The same set of data was utilized for both the training and the testing phases of the adaboost model. 30 optimal settings were found after tuning the model with a total of 50 distinct tree types. Figures 14 and 15 show the model's results. As can be observed, a training section performance of 100% is attained, outperforming the tree model in accuracy. The results of this model have correctly determined all the classification classes of slope conditions for the training section, and only in the test section and to determine class 1, it has not achieved full accuracy, which has classified class 1 with 60% accuracy.

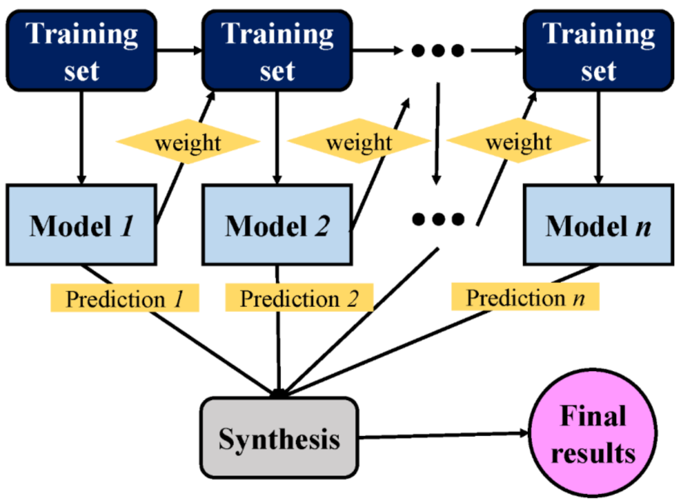

Fig. 13. An adaboost process example.

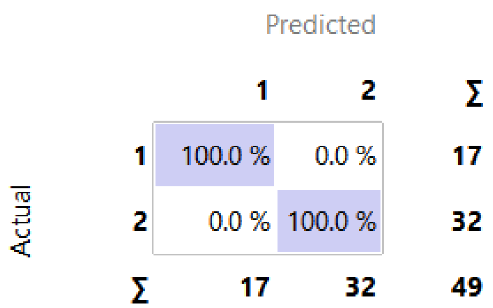

Fig. 14. The training section of adaboost confusion matrix.

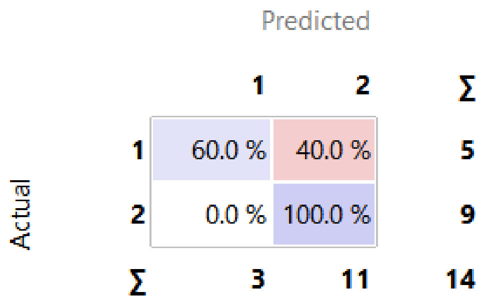

Fig. 15. The testing section of adaboost confusion matrix.

3.3. ANN modelling

Among the many nonlinear functions that can be utilized to build a system that translates input and output data [54], ANN is among the most well-known. The ANN model is different from other statistical, mathematical, and empirical methods in that it does not rely on prior information but rather on the similarities and correlations present in the data. Nonlinear activation functions and weighting are applied to a fixed number of neurons that process the inputs, resulting in an output that is a function of the input data as a whole [55]. Threshold Logic Unit has been proven to be beneficial for developing neurons by some researches [56]. Parallel groups of neurons, or nodes, perform as continuous units when building an ANN network. ANN's neurons collaborate with activation functions, with the latter's signal connecting the network's weights and nodes. The network's processing power is proportional to its structure and weights. In computers and data processing, neural networks stand out due to their unique set of features. Networks' learning algorithms are what allow us to discover robust and efficient links between the system's input and output information. Back-propagation (BP) algorithms are efficient in multilayer neural networks [57]. The BP algorithm has two main passes that it employs to go through the many layers it encounters: forward and backward. The process begins at the input layer and progresses to the output layer via the nodes and the enlargement network. A system including the weights is subjected to error correction if there is a deviation in expected output from the actual output.

Each complete data set is partitioned into two subsets, one for use in training and another for use in testing. Systems with higher performance can be tested and compared under these circumstances [58]. Several researchers [59,60] have offered suggestions on how to best put this information to use in these two chapters. Twenty to thirty percent of the data set is what they recommend as the optimal percentage to use for testing purposes. Different models are generated by the programming used to construct the ANN system. The goal is to design and convey the proposed model in the most effective way possible. The model's predictions can be tweaked by increasing or decreasing the hidden layer's neuron count. Moreover, the model learning algorithm performs admirably. The Levenberg-Marquardt (LM) method, as proposed by earlier academics, offers the optimal circumstances. There is an association between network structure and the depth of its hidden layers. The use of a hidden layer is advised for most linear and nonlinear problems [61,62] due to the difficulties seen in earlier efforts. Models benefit from a hidden layer's increased speed of convergence. The above suggests that a covert layer was employed in this analysis. Researchers have looked into how many neurons make up the buried layer. Relationships between input and output data have been proposed for a given number of neurons [63–69]. However, most studies have discovered that the optimal number of neurons to get is problem-specific, data-specific, and variable-specific. For this reason, parametric analysis is the greatest tool for determining how many neurons should be used in each hidden layer. Based on the 5 inputs, a range of 2-10 neurons was explored for each set in this research. The results of the developed model can be seen in Figures 16 and 17. When it comes to predicting and identifying landslide type, the model with 6 neurons delivers greater performance. Last but not least, the ANN model with structure (5*6*1) is chosen for this study, and the classification is then executed and reported to determine landslide conditions.

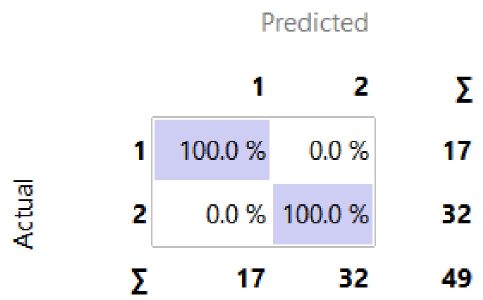

Fig. 16. The training section of ANN confusion matrix.

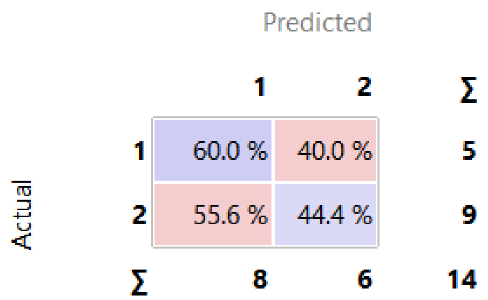

Fig. 17. The testing section of ANN confusion matrix.

4. Result and discussion

One of the key challenges in geotechnical projects is identifying the landslide conditions. landslide condition allows one to discover the many facets of stability or instability. There are a number of factors that contribute to the performance of landslide, such as its rainfall qualities and its response to soil condition. In this part, we combined the tree method, adaboost, and ANN model to establish stability or instability of landslide. According to the five characteristics listed in Table 1, the type of landslide condition can be identified. Table 2 shows the aggregated results from the testing of all available models. In the table, misclassified objects are highlighted in bold.

The poor performance of the ANN model has been demonstrated by its inaccurate classification of 7 distinct landslide types. On the other hand, two tree and adaboost models deliver satisfactory results. The adaboost model outperforms the other two in classification, with only 2 samples incorrectly classified. The results also demonstrate that the adaboost model is more precise and reliable. The number of misclassified samples, for instance, is lower when it's closer to the correct kind and provides a more reasonable response. Finally, it is demonstrated that it is a viable alternative for landslide classification through its performance relative to both tree and adaboost models.

In this part, receiver operating characteristic (ROC) analysis was used for the classification performance of the models. The sensitivity is in the y axis versus x axis (1-Specifity) in the ROC curve. The closer the graph of the models is to the upper-left corner, it means that the model has provided better performance. As can be seen in Figure 18, the two curves of Adaboost and ANN are higher than the Tree model, which shows that it has a significant performance to recognize the correct classes for landslide stability.

One of the applications of this division is the correct and deep understanding of slope stability. In the previous stage, the data was divided into two classes 1 and 2 and was implemented with different classification models. Next, category 2 samples, which include data with different ranges of movement, are predicted using the superior models.

Table 2. An overview of the landslide categorization for testing samples.

Sample	Real classification	Adaboost classification	Tree classification	ANN classification
1	2	2	2	2
2	2	2	2	**1**
3	2	2	2	**1**
4	1	1	1	1
5	2	2	2	**1**
6	1	**2**	**2**	**2**
7	2	2	2	**1**
8	1	1	1	1
9	1	1	1	**2**
10	2	2	**1**	2
11	1	**2**	1	1
12	2	2	**1**	2
13	2	2	2	2
14	2	2	2	**1**

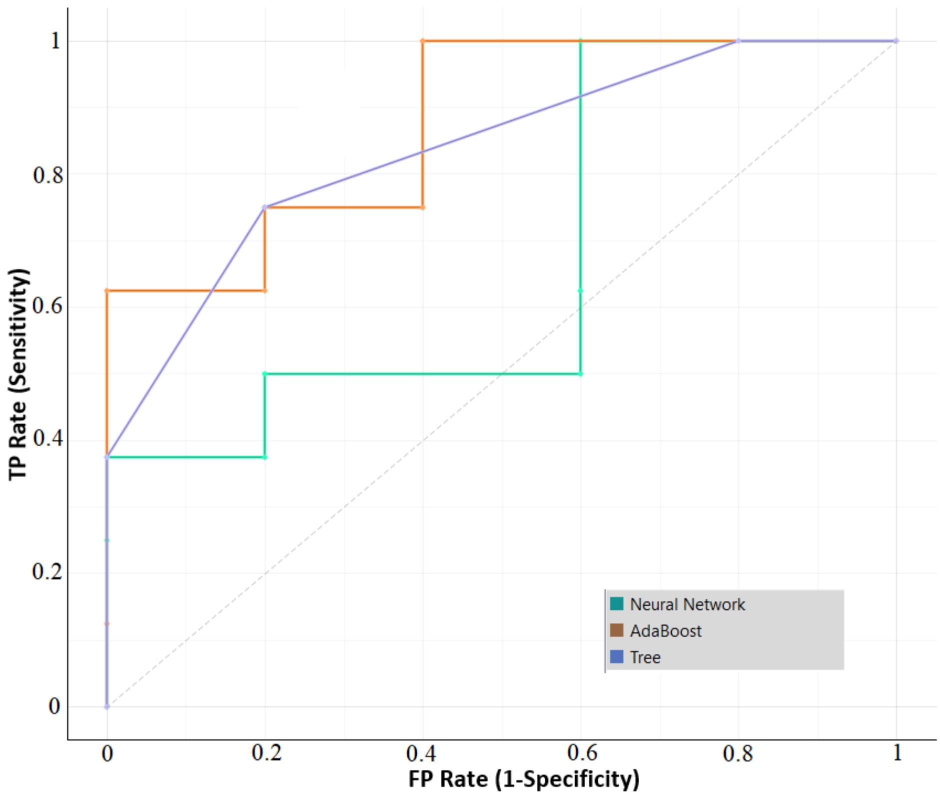

Fig. 18. The ROC for testing data.

This prediction is done by focusing on the sensitive data that have been identified, therefore, in addition to identifying areas and data prone to risk, the extent of their changes can also be estimated. The results for all data that include landslide movement are presented in Figure 19. As can be seen, with two different Adaboost model systems compared with real data, it shows acceptable accuracy. By examining the data more closely, it can be concluded that for the high-risk conditions that have landslide movement with higher values, shown in Figure 19 with arrows. These outputs can be used for optimal conditions and risk control and ultimately lead to more accurate design and management of slope stability.

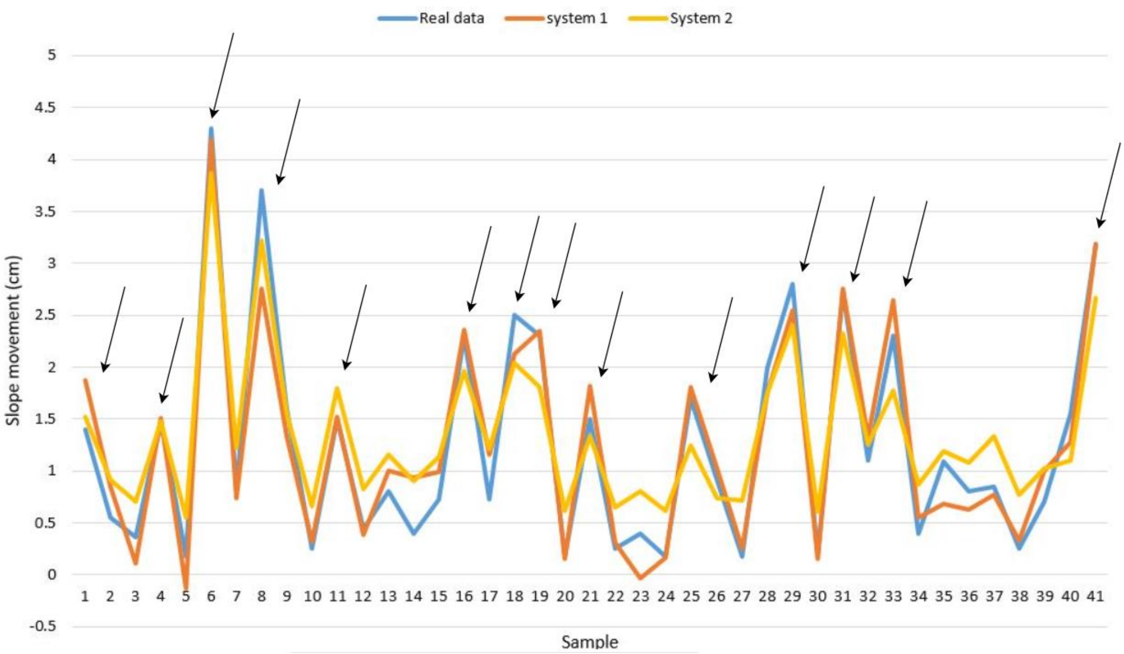

Fig. 19. The prediction of class 2 data.

5. Conclusions

Rainfall is one of the main reasons in mountainous areas that can lead to slope instability. By developing different machine learning models, this research examines and evaluates the objectives of classifying stable and unstable areas and then the amount of movement in unstable areas. The data used in this research is based on data related to mountainous areas and related to rainfall and underground water. In the first step, three different artificial intelligence models called Tree, ANN and Adaboost were used to classify stable conditions or without movement and unstable conditions or with movement. Using this division, the type of landslide condition was determined. The results of three different models were investigated with real data. In the first step, the results showed well that Adaboost and ANN models provide better performance for classifying data into two stable and unstable parts. For the test data, the Adaboost model with an accuracy of 0.857 has the highest accuracy, followed by the Tree model with an accuracy of 0.786. In addition, the ROC analysis proved that the Adaboost model can provide higher accuracy. Finally, in the second step, the application of machine learning models was developed to check and predict instability values. Acceptable results were obtained from this stage and it showed its flexibility well for conditions that are prone to sliding or moving more on the slopes.

The limitations of this research encompass the nature of the data, the quantity of data, and its constrained distribution. Given that landslides exhibit diverse conditions and are influenced by various factors across distinct geographical areas, these limitations should be acknowledged for subsequent research, thereby contributing to its comprehensiveness. Furthermore, there is a recommendation to enhance the simulation process by integrating novel optimization algorithms and leveraging their attributes to enhance the outcomes.

Conflicts of Interest

The authors declare no conflict of interest.

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