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APPLYING ARTIFICIAL NEURAL NETWORKS IN SLOPE STABILITY RELATED PHENOMENA

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Abstract

Over the past years, Artificial Neural Networks (ANN) have been successfully used for the modelling in a great number of geoscience applications. In this paper we discuss the architecture and the way ANN work, presenting a specific learning algorithm which has been applied in the estimation of landslide susceptibility within a GIS environment.
Key words: *Landslide Susceptibility, Data Mining, Artificial Neural Networks, Geographic Information System.*

Περίληψη

Τα τελευταία χρόνια, τα Τεχνητά Νευρωνικά Δίκτυα (ΤΝΔ) έχουν επιτυχώς χρησιμοποιηθεί για την μοντελοποίηση και προσομοίωση γεωλογικών διεργασιών από ένα μεγάλο πλήθος γεω-επιστημόνων. Σε αυτή την εργασία γίνεται μια συνοπτική περιγραφή της αρχιτεκτονικής και του τρόπου λειτουργίας των ΤΝΔ, παρουσιάζοντας με περισσότερη λεπτομέρεια τον αλγόριθμο οπισθόδρομης μετάδοσης σφάλματος για την εκτίμηση της κατολίσθησης επιδεκτικότητας μέσω ενός συστήματος ΓΣΠ (Γεωγραφικού Συστήματος Πληροφοριών)
Λέξεις κλειδιά: *Κατολισθητική Επιδεκτικότητα, Εξόρυξη Δεδομένων, Τεχνητά Νευρωνικά Δίκτυα, Γεωγραφικά Συστήματα Πληροφοριών.*

1. Introduction

The use of artificial neural networks (ANN) in problem solving has received considerable attention in recent years in various geo - engineering applications. This is mainly due to the capability of these networks to solve problems, in which the involved parameters are either large in number or are not fully understood. In the case of landslide hazard and susceptibility analysis, ANNs have been widely used for landslide susceptibility zonation (Lee et al., 2003, Lu & Rosenbaum, 2003, Lee et al., 2004, Ermini et al., 2005, Gomez & Kavzoglu, 2005). Different reasons of applying such methods are reported by many researchers; however their reports share a common belief that the prediction of future landslide events is based on complex, unknown, and non-linear relationships between mass movement distribution and conditioning factors (Aleotti & Chowdhury, 1999, Lee et al., 2003, Neaupane & Achet, 2004, Ferentinou & Sakellariou, 2007, Pradhan & Lee, 2010). Current research has proven that ANNs, especially multilayer perceptrons

(MLP), have several advantages when applied for landslide susceptibility mapping. A MLP can model non-linear relationships, extract useful relationships from imprecise data, and generate reasonable results even when some of the training inputs are flawed (Ermini et al., 2005, Kanungo et al., 2006). As many researchers have noted such abilities are not perfectly provided by multivariate statistical methods (Gomez & Kavzoglu, 2005, Vahidnia et al., 2010). The most widely used learning method in ANN is the back-propagation neural network, an abbreviation for "backward propagation of errors" (Rumelhart et al., 1986) and is the algorithm that will be described in this paper. The objective of the present paper is to discuss the main architecture features and the way ANN works and to present in more detail the back-propagation algorithm and how it is implemented in a landslide susceptibility analysis within a GIS environment.

2. Artificial Neural Networks

Artificial Neural Network (ANN) is considered as information – processing system capable of learning and generalizing from the "experience". Haykin (1999), described ANN as machines that are designed to model the way the human mind works when it performs a specific task. The operation of ANN is based on the following assumptions: The processing of the stimulus is carried out by a set of processing units, the neurons. Each neuron has the ability to receive and transmit a signal - the stimulus. Each signal - stimulus received or transmitted from one neuron to another in the neural network associated with a weight (synaptic weight) which indicates the strength of the connection between the respective neurons. The higher the value of the weighting factor, the more important is the contribution of the node. The sum of the received signals - stimuli, is aggregated through a function, the activation function to emit the final signal (Fausett, 1994). The most distinguished characteristic of an Artificial Neural Network is the ability to generalize (make prognosis) once trained. Thus, they are capable of "learning" from a set of data whose characteristics are known, even if the form of their relationships are unknown or their physical interpretation is difficult to be explained and after that, they can make predictions on a set of new input data. This property makes the ANNs to be more advanced against empirical and statistical methods, which require prior knowledge of the data distribution and also the nature of the relationship (linear, non – linear, etc.).

2.1. The Learning Process Method

The neural networks receive stimuli (information and knowledge) through an iterative learning process, as people do, and knowledge is stored in the network connections (Haykin, 1999). The ANN models tries to combine the thinking of the human brain with the abstract mathematical thinking, following parallel distributed processing (McClelland & Rumelhart, 1986). There are typically three types of learning, supervised, unsupervised and reinforcement learning. In supervised learning, learning is accomplished by presenting a set of training patterns each with an associated target output vector, while in unsupervised learning type, learning is accomplished by grouping a similar set of input patterns together without the use of training data to specify what a typical member of each group looks like or to which group each pattern belongs to (Fausett, 1994). Reinforcement learning is learning by interacting with an environment. A reinforcement learning model learns from the consequences of its actions, rather than from being explicitly taught. It selects its actions on the basis of its past experiences (exploitation) and also by new choices (exploration), which is essentially a trial and error learning process. The most typical ANN setting is the one that enables supervised training. During the training phase, the hidden and output layer neurons process their inputs by multiplying each input by a corresponding weight, summing the product, and then processing the sum using a non-linear transfer function to produce a result. An ANN learns by adjusting the weights between the neurons in response to the errors between the actual output values and the target output values. At the end of this training phase, the neural network provides a model that should be able to predict a target value from a given input value. In general the method used to estimate the values of the synaptic weights, trains the multilayered until some targeted minimal error is achieved between the desired and actual output values of the network. Once the training is complete, the classification phase follows, where the network is used as a feed-forward structure to produce a classification for the entire data.

2.2. The Basic Features of ANN Models

As it is evident, each neural network is characterized by three basic features (Fausett, 1994, Benardos & Benardos, 2005):

- The way in which the neurons are connected to each other, which is called the network architecture.
- The method used to establish the values of the weights on the connections, called training or learning algorithm.
- The type of activation function used.

Defining the architecture of ANN is a critical process and requires on the part of the researcher, the fullest possible knowledge of the problem application (Benardos & Kaliampakos, 2004). Neural networks are often classified as single layer or multilayer, which are examples of feed-forward networks in which the signals flow from the input units to the output units in a forward direction. In MLP networks, such as the one that is presented in this study, there is always an input layer, a hidden layer and an output layer (Figure 1). The first layer of the network, or input layer, contains a node for each of the input variables. The input variables are analogous to the independent variables in multiple regression techniques. The second layer, the hidden layer, consists of nodes that allow complexities to develop among input nodes. The last layer of the network, or output layer, contains *t* nodes, one for each output type.

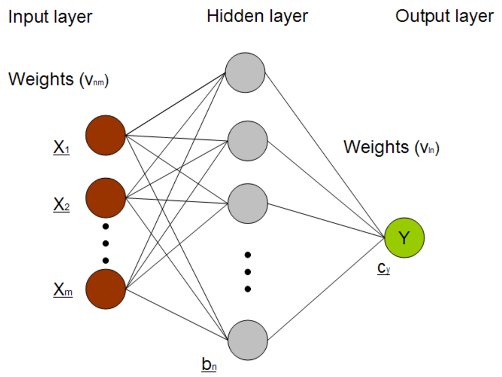


Figure 1 – The feed – forward multi-layer artificial neural network.

2.3. The Back – Propagation Algorithm

The training of an ANN by back-propagation learning algorithm involves three stages: the feed-forward of the input training pattern, the calculation and back-propagation of the associated error and the adjustment of the weights. After the training phase, application of the model involves only the computations of feed-forward phase. In the first stage, each input unit receives an input signal and transmits this signal to each of the hidden units. Each hidden unit then calculates its activation and transmits its signal to each output unit, by applying a function:

Equation 1 – the output signal of the net

$net_j^{(l)}(t) = \sum_{i=0}^{p} \left(y_i^{(l-1)}(t) w_{ji}^{l}(t) \right)$, the net input of jth neuron of layer l and t iteration

Each output unit computes its activation to form the response of the net for the given input pattern by applying the following formula:

Equation 2 – the response of the net

$$y_j^{(l)}(t) = f\left(net_j^{(l)}(t)\right)$$

Each neuron in the network may employ a nonlinear activation function at the output end, producing smooth signals to other neurons. One of most commonly used activation functions is the binary sigmoid transfer function which has range of (0, 1) and is defined as (Hagan et al., 1996):

Equation 3 – the sigmoid function

$$f(net) = \frac{1}{1+e^{(-net)}}$$

Each output unit compares it's activation with its target value to determine the associated error for that pattern with that unit.

Equation 4 – the associated error

$$e_j(t) = c_j(t) - a_j(t)$$

Based on this error, a δ factor, is computed which is used to distribute the error at output unit back to all units in the hidden and input layer.

Equation 5 – the δ factor for the output layer

$\delta_j^{(l)}(t) = e_j^{(l)}(t) a_j(t)\left[1 - a_j x(t)\right]$, δ factor or neuron jth in the output layer ith

Equation 6 - the δ factor for the hidden layer

$\delta_j^{(l)}(t) = y_j^{(l)}(t)\left[1 - y_j(t)\right]\sum_k \delta_j^{(l+1)}(t) w_{kj}^{(l+1)}(t)$, δ factor for neuron jth in hidden layer ith

After the entire δ factors have been calculated, the weights for all layers are adjusted simultaneously, according to the generalized Least – Square - Mean rue (Hagan et al., 1996):

Equation 7 – the formula for the weight estimation

$$w_{ji}^{(l)}(t+1) = w_{ji}^{(l)}(t) + \alpha\left[w_{ji}^{(l)}(t) - w_{ji}^{(l)}(t-1)\right] + \eta\delta_j^{(l)}(t) y_i^{(l-1)}(t)$$

where η is the learning rate, and α is the momentum rate for speeding up learning without running into the risk of oscillation.

There are several aspects that need to be taken into account during the construction and implementation of the back-propagation algorithm that are related to the non - deterministic nature of this method. Specifically there are several learning performance indices or cost functions that should be selected according to the related problem and they are mainly based on distance functions. Furthermore, the initial weight of the multilayer feed-forward neural network strongly influences the convergence of the back - propagation learning algorithm and so does the learning rate η. A large learning rate value speeds up the convergence but the weights may then oscillate, while a low learning rate results in slow learning. An alternative way in coping with this problem is by introducing a momentum term to the gradient – descent method, giving to each weight some inertia (momentum) is such a way that it tends to maintain its direction. Some other issues that are not always clear are firstly, the choice on the number of the hidden layers and nodes required solving a learning problem and secondly the choice on the number of the training samples required (Grima, 2000).

3. Artificial Neural Network and Landslide Susceptibility Analysis

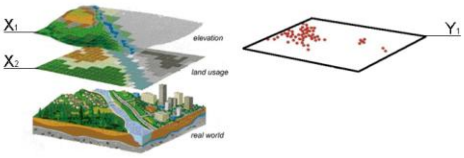
In the literature there are numerous studies that present various kinds of physical (process-based), statistical, or combined approaches for dealing with the landslide hazard and susceptibility zonation mapping (Glade et al., 2005). Landslide susceptibility is the likelihood of a landslide occurring in an area on the basis of local terrain conditions (Brabb, 1984). It is the degree to which a terrain can be affected by slope movements, an estimate of "where" landslides are likely to occur. As reviewed through the literature, there is no agreement on the methods for susceptibility maps production as several qualitative and quantitative methods have been proposed for landslide susceptibility evaluation (Carrara et al., 1995, Aleotti & Chodwdhury, 1999, Guzzetti et al., 1999, Dai et al., 2002, Glade et al., 2005).

Most of these methods share a common limitation that has to do with the difficultly to objectively handle the non-linear multivariate characteristics of the landslide phenomena that is assumed to be due to the spatial and temporal variability, scale dependency, and complicated interrelationship of the factors affecting landslide manifestation. Statistical models, such as multiple regression and discriminate function techniques, are primarily designed to deal with linear problems and therefore, may be inappropriate for assessing complex non-linear problems. The physical models require detailed spatial information about the geomechanical features of the geological and hydrological materials that are involved in a landslide susceptibility or hazard assessment. These parameters show high spatial variability and in fact are very difficult to be presented in a large scale (van Westen et al., 2006).

During the last two decades, Artificial intelligence and Data Mining techniques have been introduced as efficient tools in susceptibility and hazard analysis (Flentje et al., 2007, Kawabata et al., 2009, Tsangaratos et al., 2011). These techniques can deal with non-linear problems and, at the same time, minimizing subjectivity. One of the most promising methods is the one that use the artificial neural networks techniques. Elias & Bandis (2000) proposed a neuro-fuzzy approach for Landslide Susceptibility Zonation mapping. The authors used Fuzzy linguistic rules to assign fuzzy membership values to different classes of thematic data layers. The fuzzy membership values were used to provide data to the input neurons of a Back Propagation neural network model. A single output neuron with values from 0 to 1 was considered to represent the degree of landslide susceptibility based on actual landslide data. Lee et al. (2001) applied ANN in the Yongin in Korea to obtain a landslide hazard zonation map. The authors introduced a back-propagation algorithm twice, firstly to produce a landslide inventory map and secondly to determine the weight coefficients of each input landslide related parameter. The verification results between the calculated landslide susceptibility index and the existing landslide location data showed a good agreement and satisfactory output results. Ermini et al. (2005) applied Probabilistic Neural Network (PNN) and Multi Layered Preception (MLP) to create a landslide hazard map in Riomaggiore Italy. The researches converted the input factors to binary variables and used these variables as input data of the developed ANN model. Ferentinou & Sakellariou (2007) applied several computational intelligence tools in slope performance prediction both in static and dynamic conditions. Specifically, the used the back-propagation algorithm, the theory of Bayesian neural networks and the Kohonen self-organizing maps, for estimating the slope stability controlling variables by combining these computational intelligence tools with generic interaction matrix theory. Their study, focused on the prediction and estimation of slope stability, coefficient of critical acceleration, earthquake induced displacements, unsaturated soil classification, and the classification according to the status of stability and failure mechanism for dry and wet slopes. Caniani et al. (2008) applied the back-propagation learning algorithm within a three layered model, input, hidden and output layer, in a research area at Potenza, Italy. The authors concluded that the neural networks model that they used constituted a relatively simple solution to complex problems, such as those concerning the estimation of landslide susceptibility. However, they also reported that the knowledge acquired by the network is expressed through a set of weights and hence not in an immediately comprehensible format. They finally noted that a neural network can be progressively improved with the availability of additional information by refining the details of the input maps that are found to be the most important, according to the assessed ANN weights. Melchiorre et al. (2008) introduced an integrated use of supervised and unsupervised techniques to improve the results of neural classifiers during a landslide susceptibility analysis. The use of Cluster analysis methods and the possibility of choosing the distance measure make it possible to introduce expert knowledge to the process of landslide susceptibility analysis. Marjanovic et al. (2009) used support vector machine (SVM), neighbor k-NN algorithms and Analytical Hierarchy Process (AHP) for weighting influences of different landslide related input parameters. Authors combined multi-criteria analysis and machine learning techniques to capture the different importance of several inputs parameters and give a single outcome of the modeled landslide phenomenon. Oh & Pradhan (2011) applied the Adaptive Neuron – Fuzzy Inference System (ANFIS) for landslide susceptibility mapping in Penang Island, which is based on both expert knowledge using fuzzy inference system (FIS) and supervised learning (ANN). Landslide-susceptible areas were analyzed by the ANFIS approach and mapped using landslide-conditioning factors. The applied ANFIS model learns the “if–then” rules between landslide-related conditioning factors and landslide location, for generalization and prediction. The authors used various membership functions (MFs) for the landslide-susceptibility mapping and their results were compared with the field-verified landslide locations.

3.1. The Process of Landslide Susceptibility Analysis Through ANN Models in a GIS Environment

In recent years, GIS has become a very important tool for landslide susceptibility and hazard assessment (Carrara et al., 1995, David & Douglas 1998, Guzzetti et al., 1999, Dhakal et al., 2000, Lee et al., 2003, Glade et al., 2005). GIS is a computer-based technology designed to capture, store, manipulate, analyze, and display diverse sets of spatial data. In general there are four phases involved in the process of manipulating landslide related data through ANN in a GIS environment: the data preparation phase, the training phase, the classification phase and landslide susceptibility mapping phase, and the validation phase. The first phase consists in constructing the GIS spatial database that will be used during the landslide susceptibility and hazard analysis. The advance of GIS is that it may accept different types of variables (e.g., class, ordinal, continuous, and categorical) as input values and that it can also handle imperfect or incomplete data. The thematic data layer that refers to each factor depicts the categories of each factor (Figure 2). Each category is assigned an attribute value subjectively (expert knowledge), depending upon its relative significance in causing landslides. These attribute values must be normalized with regard to the highest attribute within the corresponding causative factor and form the input data for the ANN model. During the data preparation phase the GIS spatial database must be converted to the format of input for the artificial neural, in most cases in ASCII data format. Also, in the preparation phase the spatial data are partitioned into two subsets, the training and testing dataset. The first subset, subset of the training data, includes all the data belonging to the problem domain and is used in the phase of training that follows.



elevation		land usage	
classes	Normalized attribute	classes	Normalized attribute
1. 0 -100m	0.1	1. Class a	0.1
2. 100 - 300m	0.3	2. Class b	0.3
3. 300 - 500m	0.5	3. Class c	0.5
4. 500 - 700m	0.7	4. Class d	0.6
5. > 700m	0.9	5. Class e	0.7
		6. Class f	0.8
		7. Class g	0.9

Figure 2 – Applying ANN in a GIS environment.

The training process begins by assigning randomly initial connection weights to the input nodes which are constantly updated until an acceptable training accuracy is reached. The adjusted weights obtained from the trained network have been subsequently used to process the testing data in order to evaluate the generalization capability and accuracy of the network. The output layer of ANN contains a single neuron that represents the presence or absence of existing landslide locations (i.e., a target output of 0.9 denotes presence and 0.1 denotes absence). The next phase involves the production of the landslide susceptibility map. The artificial neural network output data must be converted to the appropriate format for the GIS spatial database. The categorization of a terrain into ordinal zones of landslide susceptibility has been regarded as a pure classification problem. The outputs of any model that adopts the ANN technique could be considered as the degree of the membership of each terrain unit with regard to the occurrence of landslide (Ermini et al., 2005). The higher the membership value, the more susceptible is the terrain unit to the occurrence of landslide and vice versa (Equation 8).

Equation 8 – Landslide susceptibility Index

$$Ls_i = f\left(\sum_{r=1}^{n} w_{ir}\, f\left(\sum_{j=1}^{m} v_{rj} u_j + b_r\right) + c_y\right)$$

where, u is the m x 1 input vector layer, y the output vector layer, n the number of neurons in the hidden layer, v and w are the weight factors, and b_r and c_y the bias values of the neurons in the hidden and output layer, respectively.

The final phase is the validation phase. In general, models for landslide susceptibility are predictions of the spatial occurrence of landslides, and their performance should be evaluated (Guzzetti et al., 2005). A landslide susceptibility assessment should be evaluated against the information used to prepare the prediction, in a way evaluate the “goodness of fit” of the produced model. Measures of goodness of fit are obtained by preparing contingency tables showing the number of incidence correctly classified and by comparing them against the cases that were misclassified by the model. To visualize the results of the verification a graph showing the model success rates is considered as appropriate (Chung & Fabbri, 1999, Guzzetti et al., 2005). The graph is formed by taking account the percentage of the study area against the cumulative distribution function of landslide area in each predicted susceptibility class. A rapid deviation of the success rate curve from the diagonal line indicates a model with high performance.

An example of the landslide susceptibility map that can be produced from the feed forward back propagation learning algorithm is seen in Figure 3 (Tsangaratos, 2012). The model had eight neurons in the input layer one hidden layer, with seven hidden neurons and one output layer. The eight neurons in the input layer correspond to the landslide related factors (geology, geological boundaries, elevation, slope inclination, slope orientation, tectonic features, hydrographic features, road network) that had been identified as causative factors in an area of high landslide manifestation in Xanthi prefecture, Greece. The model was trained using the training database that included 260 locations of landslide and non-landslide sites. A number of trials were performed using different learning rate ranging from 0.6 to 0.9. From these trials, the learning rate of 0.88 was found to be stable. When a momentum rate of 0.05 was added to the network, the convergence of the model took longer, it reached 18000 epochs, but the error was minimized. The weight for each factor that has been calculated during the training phase is then assigned to the each factor in order to estimate the landslide susceptibility index according to equation 8. The final product of which is the landslide susceptibility map, with five classes of susceptibility, namely: Very Low Susceptibility, Low Susceptibility, Medium Susceptibility, High Susceptibility and Very High Susceptibility.

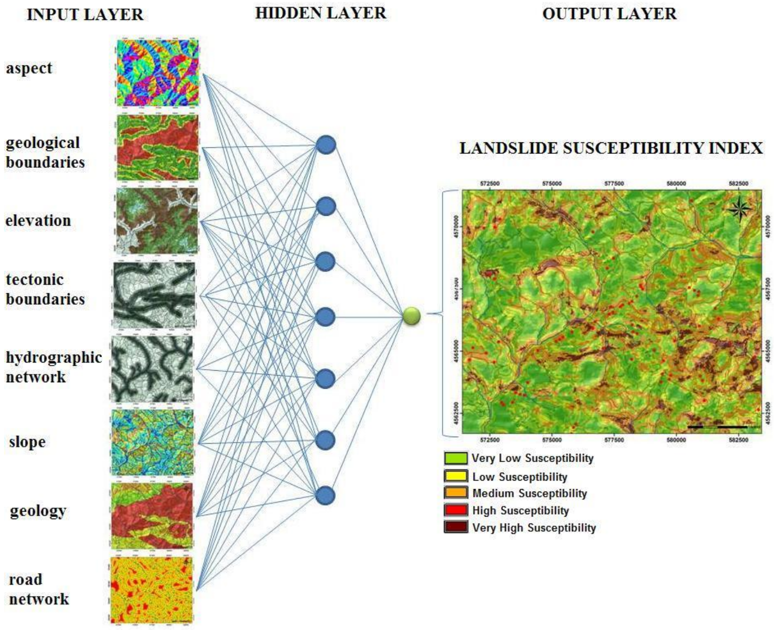


Figure 3 – The landslide susceptibility map from the feed forward back propagation neural network.

According to the methodology to validate the model, data that are not used during the training phase should be introduced to the model. By superimposing the data that formed the testing database over the landslide susceptibility map a simple validation measure of accuracy was obtained. The accuracy index, an index that corresponds to the degree of closeness of measurements of a quantity to that quantity's actual (true) value, reached 95.45%.

4. Discussion and Conclusion

In problem solving process the lack of understanding for complicated physical behaviour is easily supplemented by either over-simplifying the problem or incorporating several assumptions into the model. Consequently, many mathematical models may fail to simulate the complex behaviour of geotechnical problems. One a most promising alternatives in problem solution techniques are the non-parametric techniques that artificial intelligence and data mining domain. ANNs use learning algorithms to model knowledge and save this knowledge in weighted connections, mimicking the function of a human brain (Pradhan & Lee, 2010). They are considered as heuristic algorithms in the sense that they can learn from experience via samples and are subsequently applied to recognize new unseen data (Kavzoglu & Mather, 2000). The parallel distribution of information within the ANNs provides the capacity to model complicated, non-linear and interrelated processes. This ultimately allows ANNs to model environmental systems without prior specification of the algebraic relationships between variables (Lek et al., 1999). The most important advantage of the ANN method is that it is independent from the statistical distribution of the spatial data and there is no need for use of specific statistical variables (Lee et al., 2004). Compared with statistical methods, the ANN methods allow the target classes to be defined, taking into account their distribution in the corresponding domain of each data source (Lee et al., 2003, 2004, Zhou, 1999). Another major advantage for developing ANN process models is that they do not depend on simplified assumptions such as linear behavior or production heuristics. Neural networks possess a number of attractive properties for modeling a complex mechanical behavior or a system: universal function approximation capability, resistance to noisy or missing data, accommodation of multiple nonlinear variables for unknown interactions, and good generalization capability. Despite its simplicity and popularity, back – propagation algorithm present several problematic aspects. It may be slow and may need a considerable number of iterations to train the network. It may also be trapped easily in a local minimum and thus the learning algorithm may fail to solve the problem, independent on the network configuration. The initial weights cannot be large, otherwise the activation function becomes saturated from the very beginning and the solution will be trapped in a local minimum or a very flat plateau close to the starting point. However several researchers have proposed efficient methods that deal in an efficient way with the above mentioned aspects (Neguyen & Widrow, 1990, Nefeslioglu et al., 2010). Combining ANN techniques with GIS in a landslide analysis system can further extend the functionality of the ANN models and, at the same time, increase the set of possible applications of GIS. The major advantages of using an ANN system within a GIS environment for landslide susceptibility and hazard analysis are as follows: The collection, manipulation, and analysis of the landslide related data can be accomplished much more efficiently and cost effectively. The outcomes of the overlay functions and spatial analysis performed by a GIS can be used as the input and training conditions of a neural network and, while the results of the neural network may be manipulated by a GIS to produce a geospatial product. Each spatial input data and outcome of the neural network can be easily compiled, normalized, rescaled, re-projected and overlaid. It may accept different types of parameters (e.g., class, ordinal, continuous, and categorical) as input or output values and can handle imperfect or incomplete data. The system is extremely flexible and self-adaptive, capable of incorporating any improved new data set.

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