Hindawi
Advances in Civil Engineering
Volume 2020, Article ID 6548682, 13 pages
https://doi.org/10.1155/2020/6548682

Research Article

Bridge Seismic Damage Assessment Model Applying Artificial Neural Networks and the Random Forest Algorithm

Hanxi Jia,[1,2] **Junqi Lin**,[1,2] **and Jinlong Liu**[1,2]

[1]*Institute of Engineering Mechanics, China Earthquake Administration, Harbin 150080, China*
[2]*Key Laboratory of Earthquake Engineering and Engineering Vibration, China Earthquake Administration, Harbin 150080, China*

Correspondence should be addressed to Junqi Lin; linjunqi@iem.net.cn

Received 25 November 2019; Accepted 9 January 2020; Published 8 February 2020

Guest Editor: Chongchong Qi

Earthquakes cause significant damage to bridges, which have a very strategic location in transportation services. The destruction of a bridge will seriously hinder emergency rescue. Rapid assessment of bridge seismic damage can help relevant departments to make judgments quickly after earthquakes and save rescue time. This paper proposed a rapid assessment method for bridge seismic damage based on the random forest algorithm (RF) and artificial neural networks (ANN). This method evaluated the relative importance of each uncertain influencing factor of the seismic damage to the girder bridges and arch bridges, respectively. The input variables of the ANN model were the factors with higher importance value, and the output variables were damage states. The data of the Wenchuan earthquake were used as a testing set and a training set, and the data of the Tangshan earthquake were used as a validation set. The bridges under serious and complete damage states are not accessible after earthquakes and should be overhauled and reinforced before earthquakes. The results demonstrate that the proposed approach has good performance for assessing the damage states of the two bridges. It is robust enough to extend and improve emergency decisions, to save time for rescue work, and to help with bridge construction.

1. Introduction

Seismic events cause tremendous damage to humans and socioeconomic impacts [1–4]. In order to reduce the loss, it is necessary to formulate a postearthquake rescue plan in a timely and scientific manner [5]. However, developing a rescue plan requires an understanding of the traffic situation around the disaster area [6]. The small amount of information obtained from the postearthquake field survey cannot guide the rescue work alone. At the same time, lifeline systems have been of growing concern, especially the vulnerability to risk-induced damage [7]. The transportation infrastructure is one of the most vital lifeline systems of society [8]. If the earthquake damage assessment of the bridge can be carried out before the disaster, the traffic capacity can be quickly judged after the earthquake [9]. This can help the government and save valuable rescue time [6]. Moreover, accurate preearthquake assessments can also identify areas of earthquake resistance in the region for prevention and reinforcement, thereby reducing the potential damage caused by the earthquake. Hence, how to carry out accurate seismic damage assessment has become an important practical issue.

Although there are many factors that affect the damage of bridges, not each one has a vital role. Hence, it is vital to choose an appropriate technique to assess the importance of different factors. Linear methods are often applied to evaluate factor importance [10]. Mangalathu et al. have established the correlation between bridge fragility and factors applying the linear technique [11]. However, because of the ambiguity of each correlation feature [12], ensemble models of machine learning are raised by some studies and used for factor correlation evaluation problems [13–15] for increasing the precise and generalized performance of the empirical methods [16]. It has been proven that the results of the ensemble models are better than the empirical methods

[10]. A recent study has given the relative importance of each uncertain input parameter on the fragility curves of skewed bridges based on three-layer neural networks [11]. However, no studies have used ensemble methods to assess the feature importance in the seismic risk area. One of the most widely used ensemble learning techniques is the RF method, which has the best overall performance compared to other algorithms, such as AdaBoost, logistic regression, and Classification and Regression Tree (CART) [17].

Different methodologies have been proposed to assess the fragility [18] or the damage of a bridge. Some of the previous studies have evaluated individual bridges in detail by using different methods, such as multipoint acceleration measurement and ANNs [19], assessing the relative risks of the failure modes of a bridge and the limitations of risk priority numbers (RPNs) associated with individual failure modes [20], as well as the Bayesian method [21]. Some studies present the assessment methods of bridge components [22]. However, emergency work needs a great deal of evaluation results of bridges to be obtained in a short period of time. Most studies used linear models or some evaluation systems, for example, Risk Priority Numbers (RPNs) [20], Hazards United States Multi-Hazard (HAZUS) [23], and the Failure Mode and Effect Analysis (FMEA) system [24]. These evaluation systems can give a risk assessment of a single bridge and give specific forms of damage, such as the ineffective angle, ineffective position, and ineffective number of structures. The evaluation procedure of the seismic performance of a highway bridge is divided into three branches: topological analysis, vulnerability analysis, and traffic flow analysis [6]. The study can serve as a tool for the decision-making of postemergency response management and seismic retrofit of the highway bridge. Nevertheless, statistical models often proposed linear techniques that were assessed by establishing functions [25], which may be difficult to formulate for structures subjected to large inelastic deformations [26]. These disadvantages can be overcome by ANNs. ANNs have a good predictability even if all the attributes are mixed together to estimate demand models [11].

Owing to their accuracy, versatility, and robustness, ANNs have been applied to a variety of problems including pattern recognition, data mining, and image processing [19]. With the rapid development of artificial intelligence, many studies estimating fragility based on the ANN method have begun to emerge [27]. It was used to assess the fragility of some different bridges [11]. The multiparameter fragility methodology helps to generate fragility curves for a specific skew angle and a set of bridge parameters. However, the fragility curves are obtained in a complex manner and cannot be obtained in a few minutes [11]. The steps are as follows: (1) estimating the demand based on the ANN, (2) using the Latin Hypercube Sampling (LHS) method to estimate the capacity, and (3) using logistic regression to get fragility curves. Hence, although the estimation can help the bridge inspection workers to prioritize their recovery methods following an earthquake, it cannot help the emergency rescue work.

This study presents an approach for the damage assessment of girder bridges and arch bridges considering the different importance of the features of seismic bridge damage. Unlike previous studies on the application of ANN for single or several bridges or bridge components assessment [11], this research explores the use of ANN for estimation of the damage state of most of the bridges in the entire disaster area. Also, unlike previous studies on the application of linear regression for bridge seismic assessment [5], this research uses the machine learning techniques to select features and propose the new model, which can avoid making assumptions and using empirical formulas and even can avoid the subjective impact of expert experience.

The main contribution of this paper includes the following: (1) considering the importance of features and applying the RF algorithms as the calculation model, which provides a different viewpoint for selecting the features as the input variables; (2) the fact that the damage states of a large quantity of bridges are obtained through improved ANN models of several deep learning algorithms. It provides an alternative method for developing the traditional pre-earthquake maintenance of bridges and decision-making for postearthquake emergency rescue.

This study evaluates the importance of the features by applying the RF model and using the data from the Wenchuan earthquake in 2008. Then, the ANN damage evaluation model is processed according to the results of the previous work on a girder bridge and the arch bridge, respectively. To examine the accuracy and applicability of the assessment model, this research selects the linear regression model [5] and 40 bridges in the Tangshan earthquake in 1976. Finally, the future extensions and limitations of the proposed method are discussed.

2. Data

The 12 May, 2008, Mw7.9 Wenchuan earthquake, with wide and significant influence, had great destructive power and the aftershocks lasted for a long time. After the earthquake, the China Earthquake Administration dispatched experts to conduct on-site investigations and set up 4,150 investigation sites with an investigation area of 500,000 square kilometers [5]. The survey data are comprehensive, standardized, detailed, and complete in comparing the data of the Tangshan earthquake and the Haicheng earthquake. Therefore, they are suitable for statistical analysis, and this study used the bridge data of the Wenchuan earthquake.

The investigation scope of the Wenchuan earthquake was based on the nationally identified severely affected areas, the national trunk highways in extremely severe disaster areas, and all the bridges on some county and township roads. It covers 10 counties and cities in Sichuan, Shanxi, and Gansu provinces: Wenchuan County, Beichuan County, Mianzhu City, Shifang City, Qingchuan County, Mao County, Anxian County, Dujiangyan City, Pingwu County, and Pengzhou City, making a total of 47 highways and national highways. The survey area covers the intensity as the VI–XI degree area. The seismic precautionary intensity of the bridges in most of the hardest and most severe areas before the earthquake is VII. A total of 2,154 bridges were

surveyed: 746 in the VI degree area, 287 in the VII area, 175 in the IX degree area, and 168 in the X and XI areas. Among them, 1,525 were girder bridges and 590 were arch bridges, and the remaining bridges were cable-stayed bridges and suspension bridges. Hence, this paper chose the girder bridges and arch bridges.

The investigation is divided into three stages. (1) The emergency rushing stage was from 12 May, 2008, to 27 May, 2008. The characteristic was that it enters the disaster area for the first time after the earthquake. The seismic damage data obtained could best reflect the earthquake damage of the highway bridge after the earthquake, and the timeliness was strong. The scope of investigation was limited to the life passage leading to the most severely affected areas. Basically, no equipment was used. Experts assessed the capacity of the bridge through earthquake damage to meet emergency traffic demand. (2) The ensured bridge capacity stage was from 23 May, 2008, to the end of July 2008. The competent transportation department coordinated and arranged this, and the investigation was extensive and comprehensive, including all highways and national and provincial trunk highway bridges in the disaster area. In the investigation, the instrument was used for comprehensive testing, and the system's postearthquake bridge test report was formed. (3) The supplementary investigation stage was from August 2008 to May 2009. On the basis of the survey data and data of the first two stages of the verification, a supplementary investigation was conducted on some bridges in the first two stages, where the earthquake damage investigation was insufficient and the inaccessible areas were not included. At this stage, some roads, bridges, and municipal bridges in counties and townships were also investigated. At the same time, the bridge design data, bridge coordinates, and bridge axis directions were collected.

Table 1 shows the investigation of the main seismic damage to the girder bridges and arch bridges. Figure 1 shows the damage pictures of a typical bridge in Wenchuan County: the Caopo 3rd bridge. The first picture is before the earthquake, and the others are after the damage. The second picture in the first row presents the seventh span of the bridge moving 32 cm to the left; the first picture in the second row shows the rupture of the joint between the left block and the coping of the pier coping girder. The crack developed from the top to the left (the root is cut and penetrated). The crack is about 0.7–1.2 m, and the width is about 0.15–0.35 m. The last picture shows that the cone slopes on both sides of the abutment have local cracking, some joints fell off, the cone slope sinks as a whole, and the settlement height is 0.1–0.4 m.

3. Features

3.1. Select Features. A crucial problem in seismic damage estimation projects is whether or not the features are indeed helpful for the evaluation. There are many features influencing the damage of bridges [28–30], for example, the intensity of seismic activity, the parameters of the bridge, and the environment around the bridge. Nevertheless, some features lack sufficient data. This study selected some factors as follows: structural types, bridge pier types, foundation types, bearing types, bridge linear, bridge scales, the type of site, soil, seismic precautionary intensity, and the practical intensity of earthquakes. Table 2 presents the sorts of features.

(I) Different structural types have different reasonable spans, methods of force transmission, and principles of bearing load. Girder bridges are classified as the simply supported girder bridge, steel girder bridge (continuous girder bridge), and cantilever girder bridge in this study. A simply supported girder bridge has the following characteristics: (1) the force manners are simple and the method of force transmission is clear; (2) the deformation of the bridge cannot produce redistributed stress; and (3) the bridges are mostly used for small spans. A continuous girder bridge is suitable for larger spans and the deformability is poor with negative moment segments. Arch bridges are classified according to the material of the arch rings

(II) A bridge pier with larger stiffness is not conducive to absorbing vibration energy, and diagonal cracks will occur under seismic conditions [18], while a bridge pier with smaller stiffness is more easily deformed than the standard and becomes unstable. Therefore, the bridge pier, an important component that transmits the load from the superstructure to the foundation, has a very important influence on the bridge damage. The piers of the girder bridge are classified as five types: no pier, masonry solid pier, bent pier, rectangular thin-wall pier, and single column pier

(III) The influence of the foundation on the bridge's seismic damage is mainly due to the transmission of force [31]. Compared with the spread foundation, the open caisson foundation, and the multirow piles foundation, the bent pile foundation and tall platform pile foundation are prone to broken piles and pile detachment under the action of horizontal load. In addition, if the girder falls, it is also possible for it to break the pier or cover the pile cap. Therefore, the foundation is vital to the bridge damage

(IV) The bearings, important devices for transmitting force from the main beam to the pier, are classified as rubber bearing, steel bearing, concrete bearing, and tetrafluoroethylene bearing according to the material. The deformation capacity of the bearing has a certain influence on the bridge damage, and it is also an important component in the local seismic scheme [32–34]. For a bridge with bearing, the shock absorption support is usually used to reduce the impact of the earthquake on the bridge. The shock absorption bearing provides shock absorbers and uses the damping force generated by the viscosity of the medium or the elasticity of the rubber. Rubber

Table 1: Investigation of main seismic damage to the girder bridges and arch bridges.

Girder bridge	Superstructure and bearing	Plane displacement of the girder body, with or without girder falling, with or without potential risk of girder falling
		Impact damage of joint bridges at expansion joints
		Cracking of girder body, diaphragm, bridge deck, and hinge joint
		Bearing damage, deformation, displacement, hanging in the air, and failure of seismic anchors
		Damage of bridge deck pavement and displacement damage of expansion joint
		Damage and crack to coping, padstone blocks, etc.
	Substructure	Shearing, crushing, cracking, and tilting of the pier column
		Impact damage, cracking of the platform, and destruction of the truncated cone slope of the abutment
		Foundation displacement of piers and abutments
	Accessory structure	
Arch bridge	Superstructure	Whether the main and spandrel arch rings collapse, crack, dislocate, etc.
		Whether the vertical and horizontal connection of each arch box and the transverse connection of the arch ribs are cracked
		Whether the deck (girder) support of the girder type abdominal arch bridge is hanging in the air, displaced, and destroyed
		Whether the bridge deck is levelling and whether there is settlement on the arch fill
		Whether the side wall is cracked, extraversed, and displaced
		Whether the spandrel arch and the cross wall collapse or crack
	Substructure	Whether cracks, overturning, collapse, and settlement occur in piers, skewback, and abutments
		Cracking of the front wall and side wall of the abutment, and whether the abutment body is deformed by the earthquake force
		Whether the foundation has displacement
	Accessory structure	

Figure 1: The damage pictures of the Caopo 3rd bridge (seriously damaged; the bridge length is 225 meters).

bearing with a strong deformation ability is better than a concrete bearing with poor deformation ability. Therefore, the bearing type was also considered a factor

(V) The bridge linearity refers to the geometry of the main beam and the type of intersection angle with the riverbank. The internal force distribution of a skew bridge under external

Table 2: Features table of the girder bridge and the arch bridge (L is the length of the bridge [35]).

Features	Classification	
	Girder bridge	Arch bridge
Structural types	Simply supported girder bridge Continuous girder bridge (girder bridge of steel construction) Cantilever girder bridge	Masonry arch bridge Steel arch bridge Combined arch bridge
Bridge pier types	No pier Masonry solid pier Bent pier Rectangular thin-wall pier Single column pier Other types of piers	Masonry solid pier Other types of piers No pier
Foundation types	Shallow foundation Deep foundation	
Bearing types	Laminated rubber bearings Basin rubber bearings Tetrafluoroethylene bearings Other types of bearing No bearing	
Bridge linear	Linear orthogonal bridge (curve bridge with large curve radius) Curve orthogonal bridge Skew bridge	
Bridge scales	Small bridge ($8 \leq L \leq 30$) Medium bridge ($30 < L < 100$) Large bridge ($100 \leq L \leq 100$) Super large bridges ($L > 1000$)	
The type of site soil	I II III IV	
Seismic precautionary intensity (degree)	VI VII VIII IX VI VII VIII	
Practical intensity (degree)	IX X XI	

force is very complicated, and there are large reactions and negative moments in the obtuse angle region. There are large differences and uncoordinated internal forces between the obtuse and acute angle regions under dynamic loading in deformation and internal force. This can easily cause damage to the bridge deck. Therefore, the seismic performance of a skew bridge is much worse than that of an orthogonal bridge

(VI) Due to the large mass, a bridge with a larger span has greater inertia force under the action of seismic acceleration. The lateral load is larger, and lateral slip occurs more easily. In addition, the mid-span deflection of a bridge with a larger span is also large under the vertical load, which makes it easy for the main beam to crack or even break. Hence, the bridge scale is vital to seismic damage [11]

(VII) Site soil refers to the soil layer where the bridge is located. It can be classified as four categories. Site soil affects the bearing capacity of the foundation and the foundation failure. The failure from the class I site soil to the class IV site soil gradually increased under the same seismic intensity. Additionally, the foundation failure means that the load from the superstructure is difficult to bear on the foundation, which often causes serious damage to the bridge. Therefore, the type of site soil is also an important factor affecting the earthquake damage of the bridge

(VIII) The intensity scale consists of a series of certain key responses such as people awakening, the movement of furniture, damage to chimneys, and finally total destruction. The precautionary intensity refers to the highest intensity of earthquakes in a

certain area for many years and is the main indicator for earthquake resistance in bridge construction. Seismic precautionary intensity is an indicator that comprehensively reflects the level of bridge construction and seismic performance. It involves the effects of seismic factors such as seismic checking, layout, and local seismic components. These factors cannot be divided in detail, but they have a certain degree of influence on the seismic performance of the bridge

(IX) The practical seismic intensity is an important factor affecting the degree of bridge damage. This means the designed seismic intensity and is not associated with the design ground acceleration or peak ground acceleration (PGA) of an earthquake. Obviously, from the overall trend, the higher the seismic intensity under other conditions, the more serious the damage of the bridge. Although the results also include other factors, the degree of intensity and damage is positively correlated to the overall trend. In addition, the earthquake damage assessment must give the intensity. Therefore, the seismic intensity should be used as a factor

3.2. Default Processing. There is default value in the data set. This study chose the K-Nearest Neighbor (KNN) algorithm to treat the default value. KNN, a simple machine learning algorithm, is mainly used to solve classification problems. In the process of assuming a default value, it is necessary to calculate the Euclidean distance (equation (1)) of all the data sets for each predicted object. The Euclidean distance can describe the true distance (physical distance) of two points in n-dimensional space. There are two n-dimensional vectors $x = (x_1, x_2, x_3, \ldots, x_n)$ and $y = (y_1, y_2, y_3, \ldots, y_n)$, where x is the default value and y is the data with complete features. The Euclidean distances of x and y are expressed as

$$d(x, y) = \sqrt{\sum_{i=1}^{n} (x_i - y_i)^2}. \tag{1}$$

The results are sorted, and the K points closest to the predicted data are selected to form the decision set C. S is the default value set. We fill in the default value by averaging

$$x = \frac{1}{K}\left(\sum_{k=1}^{K}\sum_{S} C\right). \tag{2}$$

3.3. Importance of Factors. The damage states were divided into five states as per previous studies [6, 36] (Table 3): no damage, slightly damaged, moderately damaged, seriously damaged, and completely damaged. There are many seismic damage state assessment methods; for example, expert-based/judgmental, empirical, experimental, analytical, and hybrid methods. The expert-based and empirical methods do not need the demand/capacity ratio and ductility deformation ratio. The damage states of this study are based on the in situ inspections and can obtain much information about bridges quickly. The RF algorithm was proposed by Breiman [37] and had been proven to achieve suitable results in the application of feature selection [38]. The RF algorithm was chosen as the classifier to assess the importance of nine features, and the Classification and Regression Tree (CART) algorithm was applied to classify the data [14]. CART is a technique that is used in supervised learning for solving classification and regression tasks; a CART model learns simple decision rules that are inferred from the features by using a tree-like graph to demonstrate the course of actions. Each branch of a decision tree represents a possible decision, occurrence, or reaction in terms of statistical probability. The Gini index (GI_m) based feature selection can achieve both dimension reduction and the elimination of noise from the classification task [39]. The RF model was processed along with the Gini index in the Spyder module, which is a scientific Python development environment. The number of trees was classified to be 82 according to the running tests. The steps of the RF model are as follows: find the contribution of each feature on each tree in the RF, take an average, and finally compare the contribution between the features. The contribution indicates the importance of a factor. This algorithm uses VIM to represent the variable importance measures and GI to represent the Gini index. Suppose there are m features $X_1, X_2, X_3, \ldots, X_c$. Then, each feature X_j is calculated. The Gini index score is $VIM_{jm}^{(\mathrm{Gini})}$, which is the average change of the j-th feature's node splitting impurity in all RF decision trees.GI_m is expressed as

$$GI_m = \sum_{k=1}^{|K|}\sum_{k_l \neq k} PmkPmk' = 1 - \sum_{k=1}^{|K|} P^2mk, \tag{3}$$

where m is the number of the features (nodes), K is the number of classifiers, and pmk is the proportion of k in m. The change in GI_m before and after m is expressed as

$$VIM_{jm}^{(\mathrm{Gini})} = GI_m - GI_l - GI_r, \tag{4}$$

where $VIM_{jm}^{(\mathrm{Gini})}$ is the change in GI_m and GI_l and GI_r indicate the Gini index of the two new nodes after the branch, respectively. If the node where the feature j appears in the decision tree is in the set M, then the importance $VIM_{ij}^{(\mathrm{Gini})}$ of the feature j at the ith number is

$$VIM_{ij}^{(\mathrm{Gini})} = \sum_{m \in M} VIM_{ij}^{(\mathrm{Gini})}. \tag{5}$$

If there are n trees of the RF model, the importance value of the feature j, $VIM_j^{(\mathrm{Gini})}$, is expressed as

$$VIM_j^{(\mathrm{Gini})} = \sum_{i=1}^{n} VIM_{ij}^{(\mathrm{Gini})}. \tag{6}$$

Finally, all the importance scores normalized are obtained:

$$VIM_j = \frac{VIM_j}{\sum_{i=1}^{c} VIM_i}. \tag{7}$$

Table 3: The characteristics of five damage states.

Damage degrees	Characteristics
No damage	Load-bearing and non-load-bearing components are intact, or individual load-bearing components are slightly damaged and can be used without repair
Slightly damaged	Visible cracks appear in individual load-bearing components; non-load-bearing components have obvious cracks; can be used without repair or repair
Moderately damaged	Most load-bearing members have slight cracks; some have obvious cracks; some nonbearing members are seriously damaged; can be used after general repair
Seriously damaged	Most of the load-bearing members are seriously damaged; nonbearing members are partially collapsed; the repair is difficult
Completely damaged	Most of the load-bearing components are severely damaged; the structure tends to collapse or have collapsed; no repair is possible, and there is a need for reconstruction

The average accuracy (mean scores) of the classification of the random forest algorithm is 0.8304, and the standard deviation of random forest classifier is 0.0124. This accuracy is greatly improved compared with the classification accuracy of the logistic regression model, 0.7879, with the same parameters. The importance of different factors in girder bridge and arch bridge seismic damage assessment is presented in Figure 2. The range is between 0.0 (min) and 1.0 (max) for the two types of bridges. This is normalized and the sum of all features equals 1.0. During the entire RF model experiments, three experiments were selected randomly. The order of the features of the three experiments is the same, and it can be seen that the results of each time are almost the same. Figure 2 also shows the results of three experiments. The I–IX values on the abscissa represent nine features, and the ordinate is the importance value of the features. This proves that the RF algorithm can obtain a suitable evaluation of the problem of feature correlation [15].

4. Assessment Model

Seven features were selected as the variables of the girder bridge and arch bridge assessment models, respectively (Table 4). The choice of the input parameters depended on the importance of the priority, preferring more important parameters. The importances of structural types and bridge linearity were 0.014 and 0.027 of the girder bridge model. The importances of the foundation types and bridge liners were 0.004 and 0.031 for the arch bridge. The features mentioned above were not selected because of their low importance.

The Wenchuan earthquake had several characteristics that were higher than other huge earthquakes: intensity, scope of impact, and level of data collection. Therefore, there were 1525 girder bridges and 590 arch bridges of the Wenchuan earthquake in 2008 selected as the data set. The samples were preprocessed by the openpyxl function of the Anaconda Navigator environment. In the girder bridges model, there were 1300 bridges as the training set and 225 bridges as the testing set. In the arch bridges model, there were 400 bridges as the training set and 190 bridges as the testing set.

The ANN consists of an input layer, multiple hidden layers, and an output layer. Once the input data are given to the ANN, the output values are computed sequentially along the layers of the network. At each layer, the input vector comprising the output values of each unit in the layer below is multiplied by the weight vector for each unit in the current layer to produce the weighted sum. Then, a nonlinear function, such as a sigmoid, hyperbolic tangent, or rectified linear unit (ReLU), is applied to the weighted sum to compute the output values of the layer. The computation in each layer transforms the representations in the layer below into slightly more abstract representations. Based on the types of layers used in ANN and the corresponding learning method, ANN can be classified into multilayer perceptrons, which are based on the feed-forward neural network (FFNN), Stacked AutoEncoders (SAEs), or deep belief networks. For an intricate problem, the method can solve the problem well when it has 5 to 20 layers [40]. A five-layer ANN was decided due to the data set of the Wenchuan earthquake. The number of neurons in the middle layers was selected to obtain suitable and satisfactory results [41]. In order to obtain these, the running process started from 10, 3, and 2, respectively. The processes were repeated for more neurons. Through training, it was finally decided to take 40, 20, and 5 neurons as the number of neurons in the middle layers for decreasing the difficulty and training time of the method. There are several ways of controlling the training of ANN to prevent overfitting in the training phase. The most common form of regularization, L2 regularization, was chosen. Using the gradient descent parameter update, L2 regularization signifies that every weight will be decayed linearly towards zero. The hyperparameters were acquired as presented in Table 5.

The moving average model, adaptive moment estimation (Adam), and small batch gradient descent were selected as the optimization algorithms of the ANN model. The Adam method addressed problems in large data sets and high-dimensional parameter spaces [42]. It could overcome the shortcomings of random gradient descent and maintain a single learning rate to update ownership, and the learning rate did not change during the training process. It designed an independent adaptive learning rate for the parameters. The mini-batch gradient descent can overcome the shortcomings of batch gradient descent and random gradient descent [43] by dividing the data into some training pools and update the parameters according to the pool. Therefore, choosing the appropriate training pool size can achieve the

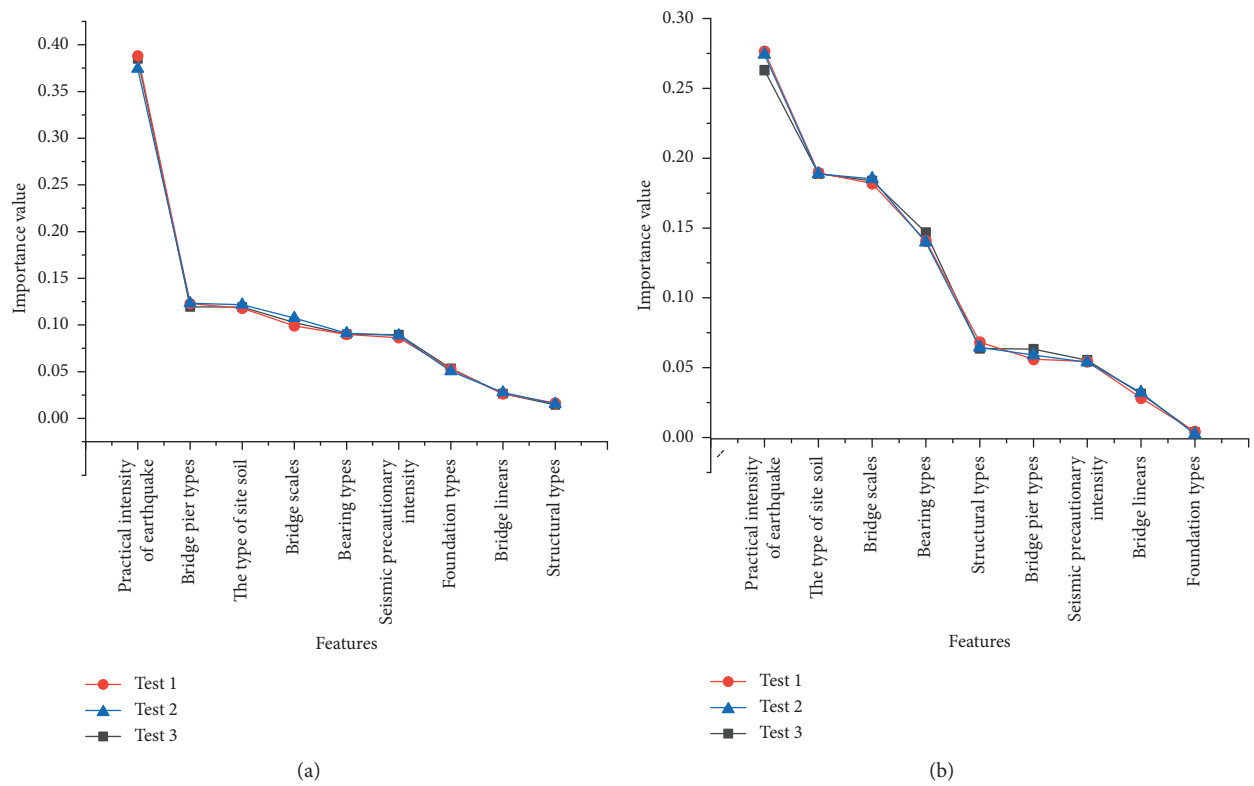

Figure 2: Processing of the girder bridge and arch bridge in random forest models: (a) girder bridge; (b) arch bridge.

Table 4: Selected features of the girder bridge and arch bridge.

Girder bridge	Arch bridge
Practical intensity of earthquakes	Practical intensity of earthquakes
Seismic precautionary intensity	Seismic precautionary intensity
The type of site soil	The type of site soil
Bridge pier types	Bridge pier types
Bridge scales	Bridge scales
Bearing types	Bearing types
Foundation types	Structural types

Table 5: Hyperparameters of the girder bridge and arch bridge models.

Hyper parameters	Mini-batch	Basic learning rate	Decay rate of the learning rate	L2	Decay rate of the moving average
Number	16	0.8	0.98	0.0001	0.99

purpose of algorithm optimization, less computation, faster calculation, improved proficiency, and accelerated convergence [44] and cannot effectively control the data of turbulence and gradient descent. The number of samples of this study was no more than 2000. Therefore, 16 bridges were decided upon for the experimental pool. The moving average model is designed to avoid mutations as the process of parameters updating [45]. This can improve the accuracy of the ANN model on the test set to a certain extent. This is achieved by the exponential moving average function in the TensorFlow framework [46], which maintains a shadow variable for each variable. The initial value of the shadow variable is the initial value of the corresponding variable, and the values of the shadow variables (w and b) are updated. The decay rate determines the update speed of the model. The greater the attenuation, the greater the proportion of shadow variables.

The TensorFlow framework [46] was used for the model. The forward propagation, structure of the network, and initial weights were decided. The normal distribution and the ReLU function [40] were chosen as the weight generating function and the activation function, respectively. The ReLU function was applied in the second and third layers. It is slightly faster to compute than other activation functions, and gradient descent does not get stuck on plateaus as much when compared to the logistic function or the hyperbolic tangent function that usually saturates at 1. The fourth layer and the fifth layer were processed as the linear regression. The Adam technique was chosen as the back-propagation method. The mean square error loss function was chosen because of the function usually being applied with the ReLU activation function.

5. Results

The results of the model were compared with those of the linear regression model based on the Wenchuan

earthquake in 2008, and equation (8) presents the regression equation (5):

$$\ln Y = \ln\left(c\prod_{i,j=1}^{n} a_{ij}^{X_{ij}}\right) = \ln c + \sum_{i,j=1}^{n} X_{ij}\ln a_{ij}, \quad (8)$$

where Y is the damage index of the bridges, corresponding to five damage levels, separately. The indexes are as follows from no damage to completely damaged: $0.00 \le Y < 0.10$, $0.10 \le Y < 0.30$, $0.30 \le Y < 0.55$, $0.55 \le Y < 0.85$, and $0.85 \le Y < 1.00$; c is the constant coefficient; and a_{ij} are the regression coefficients in the j-th subclass of the i-th class in the identified classification via Statistical Product and Service Solutions software (SPSS). Because of the collinearity problem between the independent variables, Yu selected one of each feature to set an initial coefficient and then subtracted the coefficient from the dependent variable [5]; x_{ij} is the value of the parameter of the j-th subclass in the i-th class of the bridge, the bridge meets the set parameter value of 1, and the nonconformity is 0. Table 6 presents the comparative results of the girder bridges and arch bridges between the ANN model and the linear regression model. In actual emergency rescue, it is acceptable to have a difference between the actual value and the predicted value (one level). However, if the predicted result differs from the actual value by two levels or even more than two levels, it will affect the decision of the relevant government institution. The results of the study show that the optimization algorithms have good performance in terms of improving running time. The precision of the ANN models (92.3% and 88.5%) is far greater than those in the linear regression models (71.9% and 71.5%) of an equal level. Similarly, the proportion of one level difference (5.6% and 8.2%) is much smaller than the linear model (26.4% and 27.6%). The prediction precision of the girder bridge is higher than the arch bridge for the ANN models, and the results of the two types of bridges of the linear regression model are similar.

There were 40 bridges including girder bridges and arch bridges in the Tangshan earthquake in 1976 which were chosen as the validation set. The type of site soil was deleted for the occurrence of sand liquefaction phenomena. Since this earthquake happened more than 40 years ago, the specification has been updated for generations. Therefore, the seismic precautionary intensity and the bridge scale are deleted because they are not applicable. Table 7 shows the data of 40 bridges and the prediction results. Among them, the results of a total of nine bridges are different from the true value. However, all exhibit one-level difference. The result of the four bridges is that they were seriously damaged, but the true values were moderately damaged; the other five bridges resulted to be slightly damaged, with the true value of the four bridges being moderately damaged and the other being no damage. The probability that the damage of the simply supported girder bridge is different from the true value is 5/19 (23.3%), that of the continuous girder bridge is 2/5 (40.0%), and the arch bridge is 2/16 (12.5%).

Table 6: The comparison between the ANN models and the linear regression models of the girder bridges and arch bridges (%). The results demonstrate the difference between the prediction value and the actual value of level zero, level one, and the other levels.

Differences	ANN model		Linear regression model	
	Girder bridges	Arch bridges	Girder bridges	Arch bridges
Equal	92.3	88.5	71.9	71.5
One level	5.6	8.2	26.4	27.6
≥two levels	2.1	3.3	1.7	0.9

6. Discussions

6.1. Importance of Different Features. In this study, the bridge data of the Wenchuan earthquake were used to detect the importance of different influencing factors of the two bridges applying the random forest algorithm. When analyzing a single bridge or its components, it is possible to analyze the importance of the influencing factors and take all factors into account to get better results [19]. The main purpose of this study is to analyze a large number of bridges in a certain area, so it is meaningful to conduct feature importance analysis. This fully proved the importance of the practical intensity of earthquakes, seismic precautionary intensity, the type of site soil, bridge pier types, bridge scales, and bearing types of the girder bridges and arch bridges. The importance of the six factors is more than 90% for the two bridges. Therefore, the six features mentioned above were first as the input variables. Then, the seventh feature for each of the two bridges will be discussed. The orders of importance of the characteristics of the two bridges are similar. This is because, even though the type and construction process of the bridge are different, the design principles of the bridge are the same, the components are similar, and the earthquake is the same, so the results are similar.

The foundation type is ranked seventh for the girder bridge and is ranked ninth for the arch bridge. The foundation type was used for the girder bridge model but not for the arch bridge model because the feature importance is 5% in the former and 0.4% in the latter. Besides, the results accord with the experience of some researchers. Arch structures are very sensitive to the deformations and the strength of foundations, especially in the case of earthquake (horizontal direction) load. The foundation type is vital to the seismic damage of an arch bridge. However, the result of the RF model shows that this is not important, which is the shortcoming of the model. There are many reasons for this phenomenon: (1) the more classes are distinguished by a feature, the more significant the feature is [15]. There are only two types of foundation; (2) the RF model is a black box, and the results might be different from the experience of experts, which is one of the biggest flaws of the model; (3) the results obtained by this model are of relative importance value and are the result of several feature comparisons and not the importance of independence. The structural type is

Table 7: The data of the 40 bridges and the comparison of the true value and prediction results by the ANN model for the Tangshan earthquake in 1976 (the arch bridges are specially marked and the girder bridges are not marked. "Intensity" means the practical intensity).

	Structural type	Bridge pier	Foundation	Bearing	Intensity	ANN	True value
1	Simply supported	Bent	Deep	Other	X	Seriously	Moderately
2	Simply supported	Masonary solid	Deep	Other	X	Seriously	Moderately
3	Simply supported	Masonary solid	Deep	Other	X	Seriously	Moderately
4	Simply supported	Thin-wall	Deep	Other	X	Seriously	Seriously
5	Continuous	Bent	Deep	Other	IX	Seriously	Moderately
6	Simply supported	Masonary solid	Deep	Other	IX	Moderately	Moderately
7	Simply supported	Bent	Deep	Other	IX	Moderately	Moderately
8	Continuous	Bent	Deep	Other	IX	Moderately	Moderately
9	Continuous	Bent	Deep	Other	VIII	Moderately	Moderately
10	Continuous	Bent	Deep	Other	VIII	Seriously	Seriously
11	Continuous	Bent	Deep	Other	VIII	Moderately	Moderately
12	Continuous	Bent	Deep	Other	VIII	Moderately	Moderately
13	Continuous	Bent	Deep	Other	VIII	Moderately	Moderately
14	Simply supported	Bent	Deep	Other	VIII	Moderately	Moderately
15	Simply supported	Bent	Deep	Other	VIII	Moderately	Moderately
16	Continuous	Bent	Deep	Other	VIII	Moderately	Moderately
17	Continuous	Bent	Deep	Other	VIII	Moderately	Moderately
18	Continuous	Bent	Deep	Other	VIII	Seriously	Seriously
19	Continuous	Masonary solid	Deep	Other	VIII	Moderately	Moderately
20	Simply supported	Masonary solid	Deep	Other	VIII	Moderately	Moderately
21	Simply supported	Masonary solid	Deep	Other	VIII	Moderately	Moderately
22	Continuous	Bent	Deep	Other	VIII	Slightly	Slightly
23	Simply supported	Bent	Deep	Other	VII	Slightly	Moderately
24	Simply supported	Bent	Deep	Other	VII	Slightly	No
25	Simply supported	Bent	Deep	Other	VII	Slightly	No
26	Simply supported	Bent	Deep	Other	VII	Moderately	Moderately
27	Simply supported	Bent	Deep	Other	VII	Moderately	Moderately
28	Simply supported	Bent	Deep	Other	VII	Slightly	Slightly
29	Continuous	Bent	Deep	Other	VII	Slightly	Slightly
30	Simply supported	Bent	Deep	Other	VII	Slightly	Slightly
31	Continuous	Bent	Deep	Other	VII	Slightly	Slightly
32	Simply supported	Bent	Deep	Other	VII	Slightly	Moderately
33	Continuous	Bent	Deep	Other	VII	Slightly	Slightly
34	Simply supported	Bent	Deep	Other	VII	No	No
35	Continuous	Bent	Deep	Other	VII	Slightly	No
36	Deck type (arch)	No	Deep	No	VIII	Slightly	Slightly
37	Deck type (arch)	No	Deep	No	VIII	Slightly	Moderately
38	Deck type (arch)	Bent	Deep	No	VIII	Slightly	Slightly
39	Deck type (arch)	No	Deep	No	VIII	Slightly	Moderately
40	Deck type (arch)	No	Deep	No	VIII	Slightly	Slightly

ranked ninth for the girder bridge (1%) and is ranked fifth for the arch bridge (6%). Therefore, the structural type was the factor for the arch bridge model but not for the girder bridge model. In summary, the features selected by the RF experiments are consistent with those used by other scholars to study the earthquake damage of bridges [11]. There were seven features for the two types of bridges, respectively. It can also be seen from these results that it is still meaningful to do this work. If the importance of these factors is not analyzed, less important factors are taken into account. This will greatly affect the emergency rescue time, thus increasing economic losses and casualties. At the same time, this study only removed two factors that have less impact on the two bridges. In practical applications, if a bridge in an earthquake has some factors that cannot be obtained due to some reasons, such as age, data loss, and other human factors, the corresponding influencing factors can be deleted and the model can be modified in a short time.

The RF model performs better than the other ensemble algorithms [17]. The reason for this may be that it works better with categorical features than the other methods. Also, since it uses implicit feature selection, overfitting was reduced significantly. Using logistic regression is a convenient probability score for observations. However, it does not perform well when the feature space is large, and it does not handle a large number of categorical features well. It also solely relies on transformations for nonlinear features. Using a Support Vector Machine (SVM) model, we would be able to handle a large feature space with nonlinear feature interactions without relying on the entire dataset. However, this is not very good for a large number of observations. Nevertheless, it can sometimes be difficult to find an appropriate kernel.

6.2. Assessment Model of Bridge Damage. This paper developed a bridge seismic damage state evaluation method based on previous work. The accuracy is the sum of the predicted values, and the true values differ by one or the same probability. The accuracy of the Wenchuan earthquake test is as high as 97.9%, while the accuracy of the Tangshan earthquake test is slightly reduced at 95%. The data in the training set come from the Wenchuan earthquake, so the expression on the Wenchuan earthquake test set is better. In general, this model can be used in the assessment of bridge damage in other areas, and the accuracy is acceptable. The training effect on the arch bridge is not as good as that of the girder bridge because the training set of the arch bridge is less than the girder bridge. When the predicted value is inconsistent with the true value, there is more chance of moderate damage because it occurs most frequently in the entire training set. The results of the assessment of the IX and X degrees of the practical intensity of earthquakes are always lower than the actual damage. An earthquake with a practical intensity greater than the VIII degree has a greater destructive power, and the factors affecting bridge damage are more complicated, such as earthquake secondary disasters, the bridge being been damaged before the earthquake, geological impact, and scouring effect [5]. Even if these factors have a certain impact on the bridge damage, the model does not consider these factors. This is because these factors are very complicated. Secondary disasters are difficult to obtain in the few minutes after the earthquake, and the current technology cannot accurately predict this in advance. Bridges may be eroded before the earthquake, such as by construction defects, or they are sometimes not repaired after damage from natural disasters. These conditions can only rely on daily monitoring and relevant departments should monitor the status of important bridges in time. Geological factors cannot be obtained in a short period of time, and some of them may even need to be investigated after the earthquake. The scouring effect is not considered in this study, which is one of the reasons leading to the reduction of the accuracy of the model. Erosion may cause reinforcement corrosion, spalling of concrete, and damage to foundations and platforms. However, not all the samples selected in this study were affected by scouring, so they were not considered. Hence, these factors were neglected.

The accuracy of the two bridges in the prediction of the equal level of failure and phase difference is much higher than that of the linear model [5]. The accuracy of being two levels greater or equal level is slightly lower than the linear model, but both are between 0% and 4%, which is within the acceptable range in emergency work [5]. In summary, the performance of the ANN model is better than the linear model. The reason for the small difference in accuracy between the two bridges of the linear model is that the regression technique initially has some assumptions that increase the accuracy. The ANN model does not require any assumptions throughout the process of establishment [47]. The results of the linear model must be fully calculated before they can be obtained. The ANN model can improve the training speed by setting the training rounds and steps according to the accuracy and the requirements of the specific situation, because it is more convenient and faster than the linear model.

In the practical application of the whole method, there are still some problems and challenges. (1) Since it is a rapid assessment, in addition to the speed of the model calculation, it is necessary to collect data faster. This is very difficult in practice and requires extensive experience from experts, scholars, and engineers. (2) When a bridge is less damaged, this method needs to be combined with experts and experienced decision-makers in order to improve the performance of the ANN model. (3) In practice, it is necessary to combine this method with the road to conducting an overall assessment of the road network to obtain an optimal rescue path.

6.3. Main Contributions and Significance. The method has some significance in engineering and science. The main contributions and significance of this study are as follows:

(1) The proposed method selects suitable and easily available input features based on the RF ensemble model rather than choosing features directly according to expert experiences [5] or statistical methods [11].

(2) This study uses some optimization algorithms to improve the performance of the ANN model, and the accuracy, rationality, and speed are better than the traditional back-propagation neural network [40].

(3) This study shows that an estimation of the damage states of many bridges in a few minutes can be achieved, while previous studies usually evaluate the performance of one bridge [21, 22] or some components [19].

(4) This method can be used under both preearthquake and postearthquake conditions. When it is used before an earthquake, the practical intensity of earthquakes can be obtained according to the historical maximum earthquake or seismological predictions. When the government conducts disaster prevention and mitigation planning, the formulation of relevant laws and regulations, bridge seismic damage assessment can be carried out. This can help the organization to judge the damage of bridges in the whole region on a macroscopic basis, to plan and establish the lifeline facilities in advance, and to prevent the traffic capacity of the traffic network from being affected by the damage of the bridge after the earthquake. When evaluating after the earthquake, it is possible to quickly assess the damage of the bridge in the entire earthquake zone and select the optimal path for rescue to save valuable rescue time due to the impassibility of the bridge.

7. Conclusions

The intention of this research is to propose a new model using the RF algorithm and ANN method for the evaluation of bridge

damage states. The features of girder bridges and arch bridges are assessed using the RF algorithm. The practical intensity of earthquakes, seismic precautionary intensity, type of site, soil, bridge pier type, and bridge scales are very important to the damage of the two bridges. The bearing types contribute more than the foundation types of the girder bridge, and the opposite is presented for the arch bridge. The different features are selected as the input variables in the ANN model through the results of the assessment of the feature importance. The output variables are the five damage states.

The results show that the RF model has good stability and accuracy, the accuracy and calculation speed of the ANN model are better than the linear model, and the model still performs well for other earthquakes. The proposed method of this study can serve as a tool for disaster prevention and mitigation planning, daily bridge maintenance inspections, and decision-making for postearthquake emergency response projects.

The limitations and future works of the method are as follows. (1) There are only two types of bridges in the study: girder bridges and arch bridges. Other bridges should be further investigated to make the method more applicable, such as suspension bridges and cable-stayed bridges. (2) Some features are neglected for different reasons, which will affect the applicability and accuracy of the method. The features ought to be further expanded upon to meet engineering needs. (3) The data come only from Wenchuan earthquake and Tangshan earthquake. The existing bridges in the two earthquakes were used for many years, and the performance deterioration of the materials due to corrosion and fatigue would decrease the load-bearing capacity and the ductility of the structures, consequently reducing the seismic performance and affecting the damage analysis results of the bridges. This issue should also be investigated in the future to expand the available data. (4) The RF model is a black box operation and will be influenced by the data, which might reduce the accuracy of the importance value. This issue also can be overcome by expanding the data set in the future. The model also can be improved by acting on hyperparameters or changing its architecture. For a more comprehensive analysis, additional study is needed to extend the earthquake data and determine suitable features of bridge damage.

Data Availability

The data used to support the findings of this study belong to the Ministry of Transport of the People's Republic of China and Department of Transportation of Sichuan Province. The data can be made available from the first author upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

The authors acknowledge the Department of Transportation of Sichuan Province for offering the data. This research was funded by Science Foundation of Institute of Engineering Mechanics, China Earthquake Administration (CEA) (Grant no. 2018A02) and Heilongjiang Provincial Key Laboratory of Underground Engineering Technology Open Project of China (Grant no. 2017-HXYKF-06).

References

[1] T. J. Carey, H. B. Mason, A. R. Barbosa, and M. H. Scott, "Multihazard earthquake and tsunami effects on soil–foundation–bridge systems," *Journal of Bridge Engineering*, vol. 24, no. 4, Article ID 04019004, 2019.

[2] E. Isik, M. F. Isik, and M. A. Bulbul, "Web based evaluation of earthquake damages for reinforced concrete buildings," *Earthquakes and Structures*, vol. 13, no. 4, pp. 387–396, 2017.

[3] T. K. Šipoš and M. Hadzima-Nyarko, "Rapid seismic risk assessment," *International Journal of Disaster Risk Reduction*, vol. 24, pp. 348–360, 2017.

[4] E. Isik, "Consistency of the rapid assessment method for reinforced concrete buildings," *Earthquakes and Structures*, vol. 11, no. 5, pp. 873–885, 2016.

[5] F. Yu, *Methodology for Bridge Seismic Damage Estimation Based on Wenchuan Earthquake*, Institute of Engineering Mechanics, China Earthquake Administration, Harbin, China, 2018.

[6] A. Guo, Z. Liu, S. Li, and H. Li, "Seismic performance assessment of highway bridge networks considering post-disaster traffic demand of a transportation system in emergency conditions," *Structure and Infrastructure Engineering*, vol. 13, no. 12, pp. 1523–1537, 2017.

[7] R. Twumasi-Boakye and J. O. Sobanjo, "Resilience of regional transportation networks subjected to hazard-induced bridge damages," *Journal of Transportation Engineering, Part A: Systems*, vol. 144, no. 10, Article ID 04018062, 2018.

[8] Y. Dong, D. M. Frangopol, and D. Saydam, "Sustainability of highway bridge networks under seismic hazard," *Journal of Earthquake Engineering*, vol. 18, no. 1, pp. 41–66, 2014.

[9] Z. Peng, Q. Guojin, and W. Yihuan, "Risk assessment system for oil and gas pipelines," *Energies*, vol. 12, pp. 1–21, 2019.

[10] W. Chen, Z. Sun, and J. Han, "Landslide susceptibility modeling using integrated ensemble weights of evidence with logistic regression and random forest models," *Applied Sciences*, vol. 9, no. 1, p. 171, 2019.

[11] S. Mangalathu, G. Heo, and J.-S. Jeon, "Artificial neural network based multi-dimensional fragility development of skewed concrete bridge classes," *Engineering Structures*, vol. 162, pp. 166–176, 2018.

[12] W. Chen, A. Shirzadi, H. Shahabi et al., "A novel hybrid artificial intelligence approach based on the rotation forest ensemble and naïve Bayes tree classifiers for a landslide susceptibility assessment in Langao County, China," *Geomatics, Natural Hazards and Risk*, vol. 8, no. 2, pp. 1955–1977, 2017.

[13] H.-Y. Hu, Y.-C. Lee, T.-M. Yen, and C.-H. Tsai, "Using BPNN and DEMATEL to modify importance-performance analysis model—a study of the computer industry," *Expert Systems with Applications*, vol. 36, no. 6, pp. 9969–9979, 2009.

[14] S. Park and J. Kim, "Landslide susceptibility mapping based on random forest and boosted regression tree models, and a comparison of their performance," *Applied Sciences*, vol. 9, no. 5, p. 942, 2019.

[15] F. Provost, C. Hibert, and J.-P. Malet, "Automatic classification of endogenous landslide seismicity using the Random

Forest supervised classifier," *Geophysical Research Letters*, vol. 44, no. 1, pp. 113–120, 2017.

[16] A. Altmann, L. Toloşi, O. Sander, and T. Lengauer, "Permutation importance: a corrected feature importance measure," *Bioinformatics*, vol. 26, no. 10, pp. 1340–1347, 2010.

[17] H. Jia, J. Lin, and J. Liu, "An earthquake fatalities assessment method based on feature importance with deep learning and random forest models," *Sustainability*, vol. 11, no. 10, p. 2727, 2019.

[18] S. P. Stefanidou and A. J. Kappos, "Methodology for the development of bridge-specific fragility curves," *Earthquake Engineering & Structural Dynamics*, vol. 46, no. 1, pp. 73–93, 2017.

[19] P.-j. Chun, H. Yamashita, and S. Furukawa, "Bridge damage severity quantification using multipoint acceleration measurement and artificial neural networks," *Shock and Vibration*, vol. 2015, Article ID 789384, 11 pages, 2015.

[20] F. U. Ashraf and P. A. Johnson, "Assessing relative risk for the failure modes of a bridge scour countermeasure," *Journal of Bridge Engineering*, vol. 21, no. 5, Article ID 04016010, 2016.

[21] S. Mustafa and Y. Matsumoto, "Bayesian model updating and its limitations for detecting local damage of an existing Truss bridge," *Journal of Bridge Engineering*, vol. 22, no. 7, Article ID 04017019, 2017.

[22] B. Zakeri and F. Zareian, "Bridge design framework for target seismic loss," *Journal of Bridge Engineering*, vol. 22, no. 10, Article ID 04017061, 2017.

[23] S. Mangalathu, F. Soleimani, and J.-S. Jeon, "Bridge classes for regional seismic risk assessment: improving HAZUS models," *Engineering Structures*, vol. 148, pp. 755–766, 2017.

[24] F. Franceschini and M. Galetto, "A new approach for evaluation of risk priorities of failure modes in FMEA," *International Journal of Production Research*, vol. 39, no. 13, pp. 2991–3002, 2001.

[25] L. I. N. Qingli, L. I. N. Junqi, and L. I. U. Jinlong, "A study on the fragility of highway bridges in the Wenchuan earthquake," *Journal of Vibration and Shock*, vol. 36, no. 4, pp. 110–126, 2017.

[26] N. D. Lagaros and M. Fragiadakis, "Fragility assessment of steel frames using neural networks," *Earthquake Spectra*, vol. 23, no. 4, pp. 735–752, 2007.

[27] C. C. Mitropoulou and M. Papadrakakis, "Developing fragility curves based on neural network IDA predictions," *Engineering Structures*, vol. 33, no. 12, pp. 3409–3421, 2011.

[28] K. Peng, Z. Liu, Q. Zou, Q. Wu, and J. Zhou, "Mechanical property of granite from different buried depths under uniaxial compression and dynamic impact: an energy-based investigation," *Powder Technology*, vol. 362, pp. 729–744, 2020.

[29] K. Peng, J. Zhou, Q. Zou, and X. Song, "Effect of loading frequency on the deformation behaviours of sandstones subjected to cyclic loads and its underlying mechanism," *International Journal of Fatigue*, vol. 131, Article ID 105349, 2020.

[30] K. Peng, J. Zhou, Q. Zou, and F. Yan, "Deformation characteristics of sandstones during cyclic loading and unloading with varying lower limits of stress under different confining pressures," *International Journal of Fatigue*, vol. 127, pp. 82–100, 2019.

[31] S. Soltanieh, M. M. Memarpour, and F. Kilanehei, "Performance assessment of bridge-soil-foundation system with irregular configuration considering ground motion directionality effects," *Soil Dynamics and Earthquake Engineering*, vol. 118, pp. 19–34, 2019.

[32] K. Peng, J. Zhou, Q. Zou, J. Zhang, and F. Wu, "Effects of stress lower limit during cyclic loading and unloading on deformation characteristics of sandstones," *Construction and Building Materials*, vol. 217, pp. 202–215, 2019.

[33] K. Peng, Y. Wang, Q. Zou, Z. Liu, and J. Mou, "Effect of crack angles on energy characteristics of sandstones under a complex stress path," *Engineering Fracture Mechanics*, vol. 218, Article ID 106577, 2019.

[34] P. Kang, L. Zhaopeng, Z. Quanle, Z. Zhenyu, and Z. Jiaqi, "Static and dynamic mechanical properties of granite from various burial depths," *Rock Mechanics and Rock Engineering*, vol. 52, no. 10, pp. 3545–3566, 2019.

[35] Ministry of Transport of the People's Republic of China, *General Specifications for Design of Highway Bridges and Culverts*, Ministry of Transport of the People's Republic of China, Beijing, China, 2015.

[36] J. M. Andrić and D. G. Lu, "Fuzzy methods for prediction of seismic resilience of bridges," *International Journal of Disaster Risk Reduction*, vol. 22, pp. 458–468, 2017.

[37] L. Breiman, "Random forests," *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.

[38] G. O. Gutiérrez-Esparza, M. Vallejo-Allende, and J. Hernández-Torruco, "Classification of cyber-aggression cases applying machine learning," *Applied Sciences*, vol. 9, no. 9, Article ID 1828, 2019.

[39] B. H. Menze, B. M. Kelm, R. Masuch et al., "A comparison of random forest and its Gini importance with standard chemometric methods for the feature selection and classification of spectral data," *BMC Bioinformatics*, vol. 10, pp. 1–16, 2009.

[40] Y. Lecun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, 2015.

[41] H. Aghamohammadi, M. S. Mesgari, A. Mansourian, and D. Molaei, "Seismic human loss estimation for an earthquake disaster using neural network," *International Journal of Environmental Science and Technology*, vol. 10, no. 5, pp. 931–939, 2013.

[42] D. P. Kingma and J. lei Ba, "Adam: a method for stochastic optimization," in *Proceedings of the ICLR*, pp. 1–15, San Diego, CA, USA, May 2015.

[43] K. Gimpel, D. Das, and N. a. Smith, "Distributed asynchronous online learning for natural language processing," in *Proceedings of the Conference on Computational Natural Language Learning (CoNLL)*, pp. 213–222, Uppsala, Sweden, July 2010.

[44] G. Danner and M. Jelasity, "Fully distributed privacy preserving mini-batch gradient descent learning," in *Proceedings of the IFIP WG 61 International Conference on Distributed Applications & Interoperable Systems*, vol. 9038, pp. 30–44, France, July 2015.

[45] S. E. Said and D. A. Dickey, "Testing for unit roots in autoregressive-moving average models of unknown order," *Biometrika*, vol. 71, no. 3, pp. 599–607, 1984.

[46] M. Abadi, P. Barham, J. Chen et al., "TensorFlow: a system for large-scale machine learning," in *Proceedings of the 12th USENIX Symposium on Operating Systems Design and Implementation*, Savannah, GA, USA, November 2016.

[47] A. Ferreira, L. Bondi, L. Baroffio et al., "Data-driven feature characterization techniques for laser printer attribution," *IEEE Transactions on Information Forensics and Security*, vol. 12, no. 8, pp. 1860–1873, 2017.