4-2020

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Seyed Hooman Ghasemi
Rowan University, ghasemi@rowan.edu

Hossein Bahrami

Mahdi Akbari

Journal of Soft Computing in Civil Engineering 4-2 (2020) 13-21

Contents lists available at SCCE

Journal of Soft Computing in Civil Engineering

Journal homepage: www.jsoftcivil.com

Classification of Seismic Vulnerability Based on Machine Learning Techniques for RC Frames

S.H. Ghasemi[1*], **H. Bahrami**[2], **M. Akbari**[2]

1. Department of Civil and Environmental Engineering, Washington State University, Pullman, United States
2. Faculty of Civil Engineering, Semnan University, Semnan, Iran

Corresponding author: *seyedhooman.ghasemi@wsu.edu*

https://doi.org/10.22115/SCCE.2020.223322.1186

ARTICLE INFO

Article history:
Received: 14 March 2020
Revised: 25 April 2020
Accepted: 25 April 2020

Keywords:
Damage state;
Reinforced concrete;
Machine learning;
Classification;
Redundancy.

ABSTRACT

Seismic vulnerability means the inability of historical and monumental buildings to withstand the effects of seismic forces. This article presents a classification model to specify the damage state of the Reinforced Concrete (RC) frames based on a collection of datasets from the damaged buildings in Bingol earthquake of Turkey for use in the learning process of the algorithm. The proposed model uses two classifiers including the redundancy and also the construction quality of the buildings to estimate the class of damage from four categories including none, light, moderate and severe. The available database of the considered earthquake includes the information of 27 damaged RC buildings which are published in the literature. The model provided a simple structure for engineers to predict the class without complex calculations in which it needs a few steps to determine the class of damage for RC frames. The results show that the presented model can estimate the class of each input vector with an acceptable error.

1. Introduction

One of the most critical issues in civil engineering is the seismic assessments and vulnerabilities of the structures. This issue is particularly difficult due to the numerous influential parameters

How to cite this article: Ghasemi SH, Bahrami H, Akbari M. classification of seismic vulnerability based on machine learning techniques for RC frames. J Soft Comput Civ Eng 2020;4(2):13–21. https://doi.org/10.22115/SCCE.2020.223322.1186.

and inherent complexities of the earthquake phenomenon. There are numerous studies on this topic in various references, mainly based on nonlinear analysis and attention to structural parameters. Most of the recent studies are done to determine the fragility curves of frames [1]. However, given the widespread use of such studies, especially for the strengthening of the structures, the use of new methods for the above purpose is not unexpected.

Today, machine-based learning methods are widely used in complex problems. In civil engineering, the capabilities of different branches of machine learning have been studied to evaluate and determine the capacity of structural elements by many researcher [2–14]. This is due to various reasons, including the verification of models that must be considered in order to ensure the accuracy of the results [15]. In this paper, the machine learning approach is used to create a classification model based on empirical information. The above model, based on some classifiers and without performing mathematical calculations, can estimate the damage state of concrete buildings. This model does not require complex computation to provide the output. It only specifies the output class by performing a few comparisons using classifiers. Details of the proposed model are presented in the following sections.

2. Database

A collection of 27 datasets are gathered from the work of Tesfamariam and Saatciouglu [16]. This database is extracted from the information of the buildings which are excited by the Bingol earthquake in Turkey, 2003. After creating several models to find the best parameters, two classifiers including redundancy and the construction quality (CQ), are considered to make the model. Table 1 presents the datasets of the 27 frames. The output classes for damage states are none, light, moderate and severe (Table 2). Fig. 1 and 2 present the distribution of each classifier. More details about the database can be seen in Fig. 3 to 5.

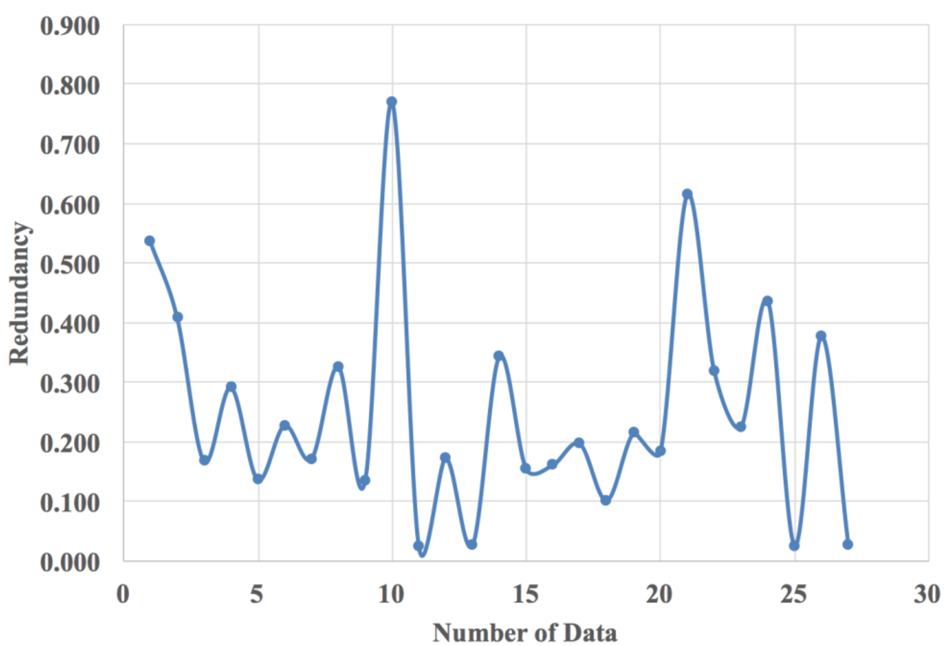

Fig. 1. The values of redundancy for each dataset.

Table 1
Database [16].

Building ID	Redundancy (R)	Construction Quality (CQ)	Damage State (DS)
BNG-10-3-10	0.536	Poor	M
BNG-10-3-3	0.408	Poor	M
BNG-10-4-4	0.167	Average	M
BNG-10-4-6	0.291	Average	L
BNG-10-4-7	0.136	Average	L
BNG-10-4-9	0.227	Good	N
BNG-10-5-1	0.171	Average	M
BNG-10-5-11	0.326	Average	L
BNG-10-5-2	0.134	Good	L
BNG-11-2-3	0.770	Poor	M
BNG-11-4-1	0.024	Poor	S
BNG-11-4-2	0.172	Poor	S
BNG-11-4-4	0.026	Poor	M
BNG-11-4-5	0.343	Average	L
BNG-3-4-1	0.154	Poor	L
BNG-3-4-2	0.161	Average	N
BNG-3-4-4	0.196	Average	N
BNG-5-5-1	0.101	Average	L
BNG-6-2-8	0.214	Poor	S
BNG-6-3-1	0.183	Average	M
BNG-6-3-10	0.615	Good	N
BNG-6-3-11	0.319	Average	N
BNG-6-3-12	0.225	Average	L
BNG-6-3-4	0.436	Average	L
BNG-6-4-2	0.025	Poor	S
BNG-6-4-5	0.377	Good	N
BNG-6-4-7	0.026	Poor	S

Table 2
Definition of the parameters.

Damage State Definition	Notation
None	N
Light	L
Moderate	M
Severe	S

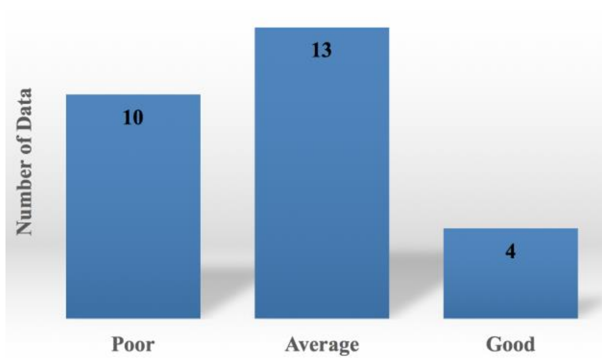

Fig. 2. The number and the linguistic values of CQ for the datasets.

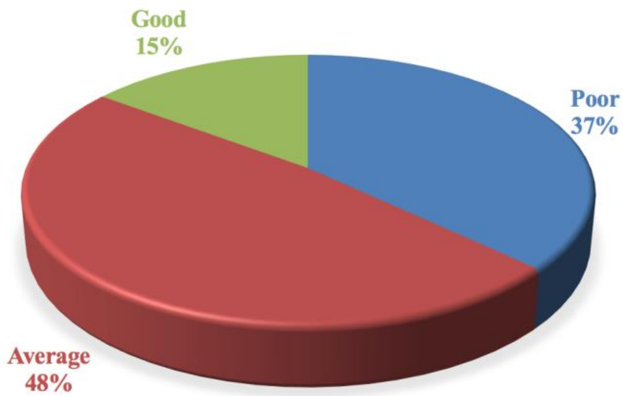

Fig. 3. Percentage of the values for the construction quality (CQ).

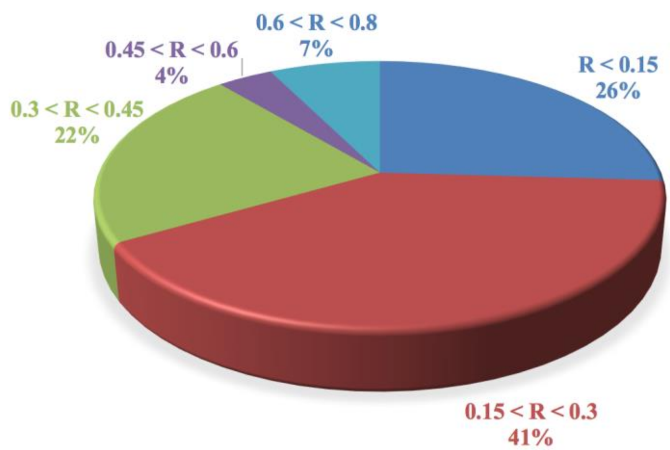

Fig. 4. Percentage of the values for redundancy.

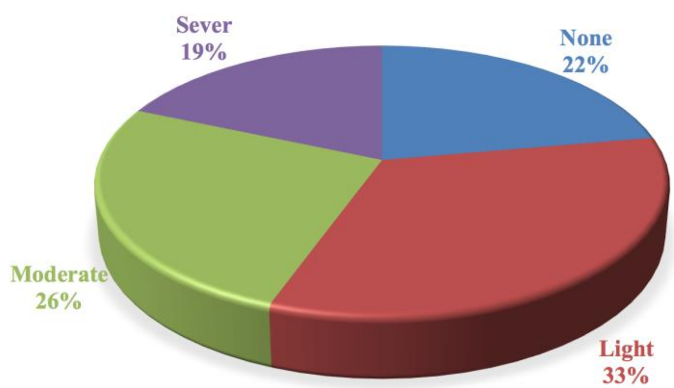

Fig. 5. Percentage of the values for the output.

3. Classification of seismic vulnerability

The method used to determine the damage state in this paper is based on knowledge extraction from a set of the collected database. These data are adjusted based on the results and observations of reinforced concrete structures that were excited by the Bingol earthquake in Turkey. Using these datasets, a decision three is determined by a machine learning approach. This model presents the class of the damage state from none to sever classes. This structure begins by applying the construction quality (CQ) as the first input variable and then defines the output variable class by performing some comparisons between the amount of redundancy and also CQ, without complicated mathematical calculations. The proposed structure is presented in Fig. 6. It is worth to mention that MATLAB software and its decision tree toolbox is used in setting the proposed model.

4. Results of the model

Using the flowchart shown in Fig. 6 and applying the collected datasets to the proposed system, the class of each input vector can be determined. To this end, two classifiers including CQ and redundancy, are used, the output of which is visible in Table 3 for each dataset. In this table, the actual damage state and the predicted classes are presented for better comparison.

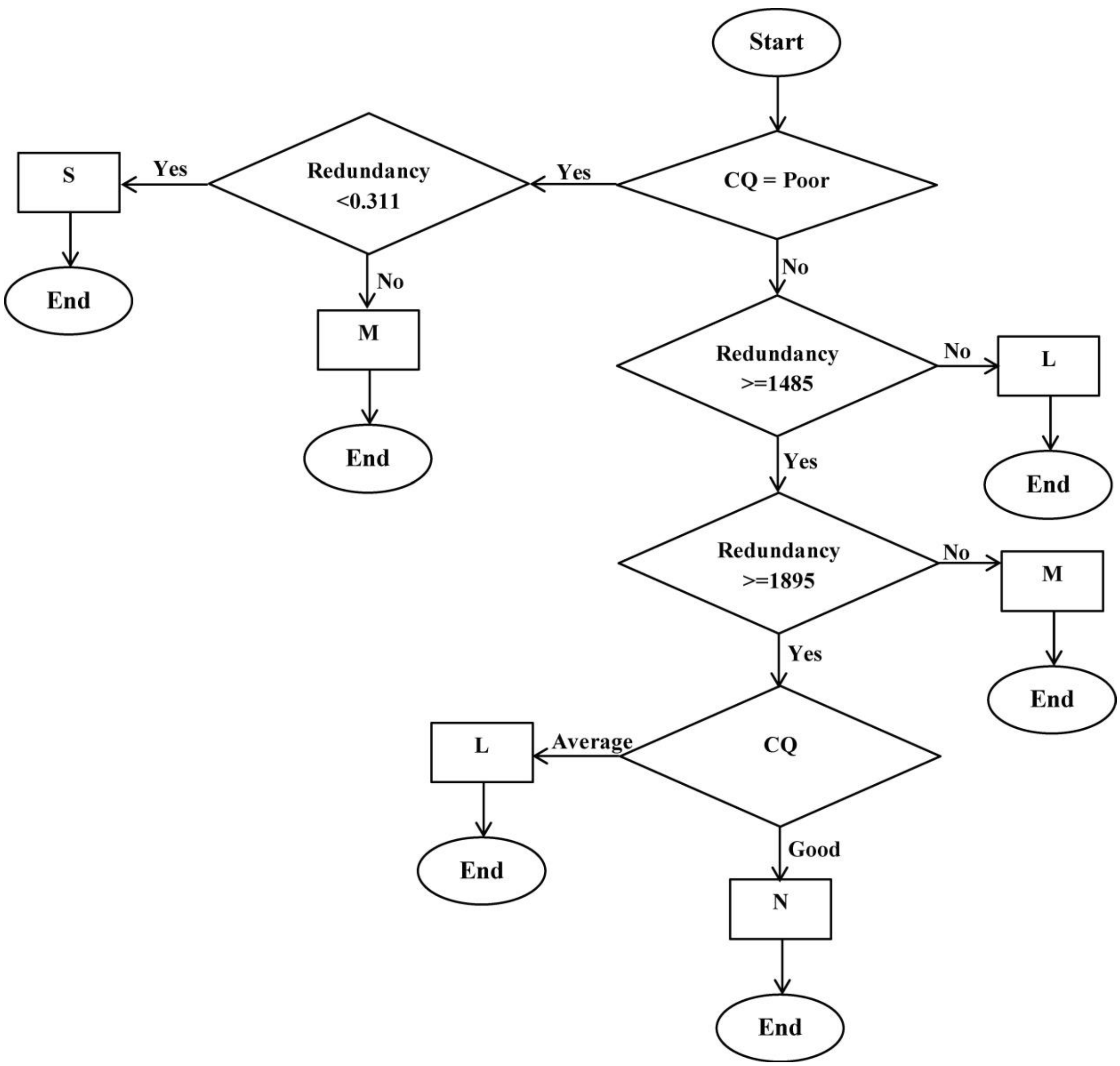

Fig. 6. The proposed flowchart to specify the class of damage state.

Table 3
The results of the proposed model in comparison with the real class for each data.

Building ID	Damage State	Predicted	Result
BNG-10-3-10	M	M	True Class
BNG-10-3-3	M	M	True Class
BNG-10-4-4	M	M	True Class
BNG-10-4-6	L	L	True Class
BNG-10-4-7	L	L	True Class
BNG-10-4-9	N	N	True Class
BNG-10-5-1	M	M	True Class
BNG-10-5-11	L	L	True Class
BNG-10-5-2	L	L	True Class
BNG-11-2-3	M	M	True Class
BNG-11-4-1	S	S	True Class
BNG-11-4-2	S	S	True Class
BNG-11-4-4	M	S	Wrong Class
BNG-11-4-5	L	L	True Class
BNG-3-4-1	L	S	Wrong Class
BNG-3-4-2	N	M	Wrong Class
BNG-3-4-4	N	L	Wrong Class
BNG-5-5-1	L	L	True Class
BNG-6-2-8	S	S	True Class
BNG-6-3-1	M	M	True Class
BNG-6-3-10	N	N	True Class
BNG-6-3-11	N	L	Wrong Class
BNG-6-3-12	L	L	True Class
BNG-6-3-4	L	L	True Class
BNG-6-4-2	S	S	True Class
BNG-6-4-5	N	N	True Class
BNG-6-4-7	S	S	True Class

It is clear from the tables above that the proposed model correctly classifies the datasets with the damage state of severe. There was also only one error for data with damage states of light and moderate. For the data reported in the database without damage (none), 3 out of 6 data were associated with an error. The above details are also provided in Table 4.

Table 4
Results of the proposed classification model.

Parameter	Damage State			
	None	Light	Moderate	Sever
Number of class in the database	6	9	7	5
Number of True class	3	8	6	5
Error (in percent)	50%	88.9%	85.7%	100%

In Fig. 7, the number of classes available for each of the damage state modes is shown along with the number of predicted classes, which are classified correctly. Accordingly, the model is highly accurate in estimating the damage state of the fourth class (sever) in comparison with other classes. Also, the proposed model has a suitable performance for light and moderate classes. In Fig. 8 a summary of the results can be seen.

Fig. 7. The classes of the datasets (true and wrong classes predicted by the proposed model).

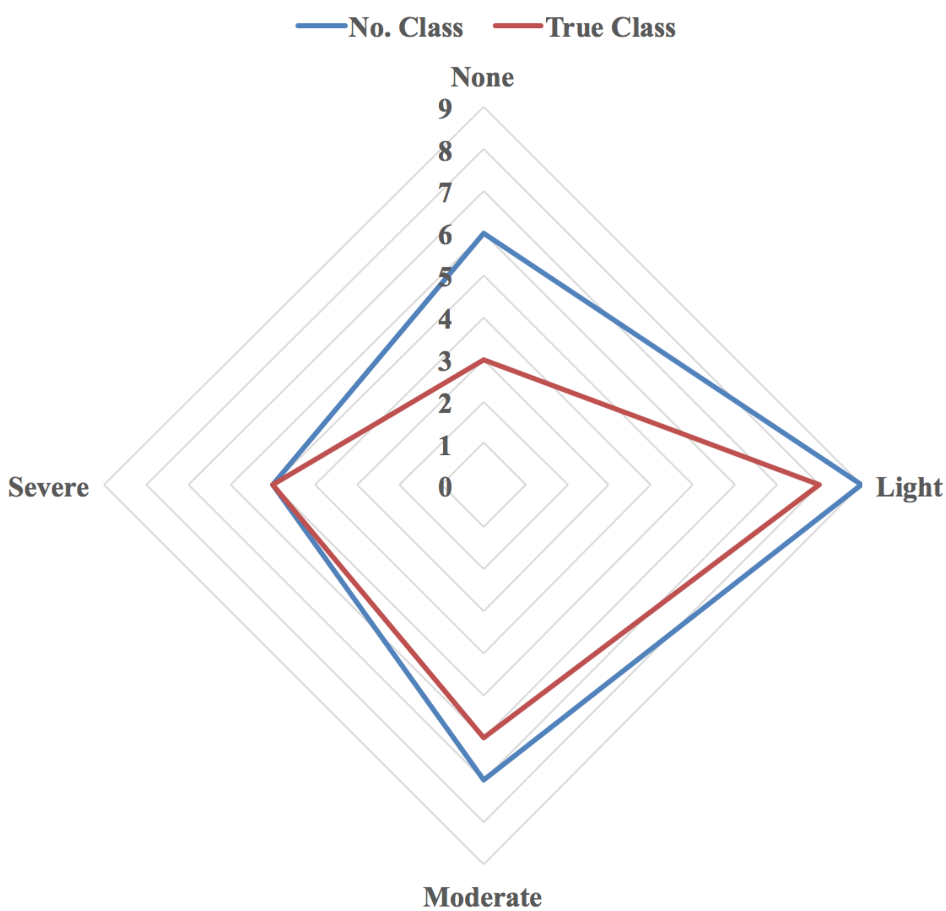

Fig. 8. Predicted classes.

5. Conclusion

In this paper, a classification system is presented that uses two classifiers including redundancy and construction quality, to estimate the damage state of the reinforced concrete buildings. This model is based on a set of data collected from a number of a building that was subjected to seismic loads of an earthquake in Turkey. In adjusting the structure of the proposed model, the above data and knowledge-based learning algorithms have been used. In general, the type of output in the proposed model is damage state of the buildings, which is classified in grades 1 to 4 (none, light, moderate, severe). The results show that the proposed model, with using simple computations, can provide the output class with the desired accuracy only with a few simple comparisons. The main application of the method presented in this paper is a rapid assessment of structures after earthquakes.

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