ESCUELA DE CONSTRUCCIÓN CIVIL
FACULTAD DE INGENIERÍA
Revista de la Construcción
Journal of Construction

Research Article

A decision tree-based damage estimation approach for preliminary seismic assessment of reinforced concrete buildings

Ayşe Elif Özsoy Özbay [1],*

[1] Civil Engineering Department, Maltepe University, İstanbul (Türkiye), ayseelifozsoyozbay@maltepe.edu.tr
*Correspondence: ayseelifozsoyozbay@maltepe.edu.tr

Received: 16.06.2021; **Accepted:** 07.12.2022; **Published:** 30.04.2023

Citation: Özsoy Özbay A.E. (2023). A decision tree-based damage estimation approach for preliminary seismic assessment of reinforced concrete buildings. Revista de la Construcción. Journal of Construction, 22(1), 5-15. https://doi.org/10.7764/RDLC.22.1.5.

Abstract: This study aims to introduce an earthquake-induced damage classification approach for seismic vulnerability assessment of reinforced concrete buildings. Through the use of the damage data collected from post-earthquake inspections after the 2003 Bingöl Earthquake in Turkey, two models were constructed by the decision tree classification technique considering nine building-specific features as the estimation variables in the analysis. The first model was developed for the prediction of the observed damage states of the buildings, whereas the second one concerning the life safety level assessment, was proposed for distinguishing the extremely vulnerable buildings for seismic prioritization. In the validation process, the leave-one-out cross validation technique was adopted to deal with the small sample size of the building inventory. Among the estimation variables, the priority index and the existence of short columns were found to have the highest importance in classification. Results have revealed that the proposed model for life safety level assessment was capable of discriminating the cluster of severely damaged and collapsed buildings from the entire database with an accuracy of 70.59%. Hence, the damage classification approach adopted in this study has the potential for improving effective tools for seismic risk assessment of the existing buildings.

Keywords: seismic vulnerability assessment, decision trees, reinforced concrete buildings, earthquake damage estimation, seismic risk prioritization.

1. Introduction

In recent decades, seismic prone countries have suffered severe damage from strong earthquakes leading to considerable economic and social impacts on the communities (Kocaeli,1999; L'Aquila, 2009; Haiti, 2010; Chile 2010; Gorkha, 2015, etc.). Such devastating earthquakes threatening millions of people underlined the demand for well-organized pre-earthquake activities for the seismic risk evaluation of large numbers of buildings. Thus, the major issue of concern for large-scale seismic evaluation activities is to introduce viable schemes to rank and prioritize the most vulnerable set of buildings that require immediate intervention for detailed seismic evaluation (Yıldızlar, Akcay & Öztorun, 2018).

Over the past decades, great efforts have been devoted to improve seismic vulnerability assessment procedures for the built environment through a variety of analytical and statistical approaches. The analytical procedures in the literature involve comprehensive numerical models to quantify the seismic risk of the buildings considering the seismic demand and capacity of the structures which require detailed physical information. Among the regional risk assessment tools, HAZUS (2012), ELER (2010) and SELENA (2010) offer standardized methodologies to estimate the probable damage state of a building by means of fragility curves derived for generic building types at a certain level of seismic action. Along with these procedures, macroseismic methods consider an intensity based vulnerability assessment to estimate the damage grade of the buildings owing to the statistical analysis of a variety of data sets acquired during post-earthquake inspections conducted on the damaged buildings (Grünthal, 1998; Lagomarsino & Giovinazzi, 2006).

The macroseismic methods mainly rely on the evaluation of seismic vulnerability concerning the constructive features and the building typology at a particular seismic intensity expressed through the macroseismic scales in EMS-98 (Grünthal, 1998). The evaluation procedure was originally introduced by Lagomarsino & Giovinazzi (2006) employing the classical probability and the fuzzy-set theory to correlate the seismic performance of building typologies with the vulnerability classes with reference to the definitions given in the European Macroseismic Scale (Grünthal, 1998). Taking advantage of the probabilistic aspects of the macroseismic methods, the philosophy behind the empirical approach has also enabled elaborations in the methodology through the use of post-earthquake damage data gathered from the buildings. In line with this, researchers employed on-site observations from post-earthquake field surveys in order to modify the existing seismic vulnerability evaluation procedures for different building typologies (Tomás, Ródenas & García-Ayllón, 2017; Rapone, Brando, Spacone & De Matteis, 2018; Ródenas, García-Ayllón & Tomás, 2018).

Wide set of post-earthquake data gathered through building damage surveys provides a valuable information for calibration of vulnerability assessment procedures which enable evaluation of building aggregates and prioritization of the buildings that require further assessment. Thus, well-organized post-earthquake field studies enable refinements in the existing empirical methods and also, constructing predictive statistical models for vulnerability assessment using the reliable damage data collected from on-site observations. Along these lines, several methods were formerly introduced for the seismic risk evaluation of reinforced concrete buildings utilizing a variety of statistical techniques as multiple linear regression and discriminant analysis in order to correlate the observed damage state with the inspected structural properties of the building (Yücemen, Özcebe & Pay, 2004; Sucuoğlu, Yazgan & Yakut, 2007; Jain et al., 2010; Özhendekci & Özhendekci, 2012). Apart from the schemes improved by regression models, attempts have also been made to introduce the preliminary evaluation methods implementing fuzzy rule based systems (Demartinos & Dritsos, 2006; Tesfamariam & Saatcioglu ,2008; Şen, 2010; Tesfamariam & Saatcioglu, 2010; Harirchian & Lahmer, 2020). Due to the fact that the actions taken during the screening process require subjective views of the surveyor, in these methods, the decisions about the seismic risk level of the building in the preliminary stage are made through the execution of a set of fuzzy rules defining the linguistic expert information and the numerical data related to the structural properties.

With the same purpose to improve efficient methods for pre-earthquake evaluation of the buildings, previous research in the literature also focused on the application of the statistical learning techniques to predict the potential damage to the buildings from the post-earthquake damage data. Among these studies, Tesfamariam & Liu (2010) utilized different classification algorithms to categorize the seismic induced damage data and discussed the effectiveness of the damage classification comparing the performance of the alternative approaches. Also, Mangalathu, Sun, Nweke, Yi & Burton, (2020) investigated the performance of discriminant analysis, k-nearest neighbour, decision tree and random forest algorithms using the post-earthquake inspection of the buildings where damage was characterized through the discrete categories prescribed in ATC-20 (1995). The results of this study revealed that random forest-based model performed better in damage prediction achieving a comparatively higher accuracy than the other techniques. Furthermore, among the learning-based methods, support vector machine was also addressed as an efficient technique in damage classification problems where the main concern is to improve efficient methods for vulnerability assessment of existing buildings (Harirchian et al., 2020, Harirchian, Lahmer, Kumari & Jadhav, 2020).

An overview of the literature reveals, great efforts are being devoted to improve pre-earthquake assessment methodologies through the implementation of statistical techniques to derive efficient models using the observed damage states and the structural properties gathered through post-earthquake damage inspections of the buildings. Yet, there exists a research gap in refining the existing methodologies and minimizing the uncertainties in the predictive models that arise from the damage data gathered during inspections.

With this motivation, this study aims to introduce a pre-earthquake evaluation scheme to predict the potential damage state and seismic vulnerability of the buildings using the damage data collected from post-earthquake on-site observations. To this aim, decision tree-based learning approach has been adopted to generate prediction models using the observed damage states as the response variables and the inspected building parameters as the estimation variables of the classification problem. The damage data used in the analysis consist of 85 reinforced concrete buildings which have been derived from the plan views and the information gathered from the damaged buildings during the field surveys conducted after 2003 Bingöl Earthquake in Turkey (Mw=6.4). Building-specific features utilized as the estimation variables were total floor area (AT), number of stories (N), priority index (PI), normalized lateral stiffness index (NSTFI), normalized redundancy ratio (NRR), existence of short columns (SH), overhang ratio (OR), pounding effect (PE) and soft story irregularity (SSI). To overcome the limitations regarding the small sample size of the building inventory, a leave-one-out cross validation was adopted in the validation process. With the implementation of the decision tree-based evaluation schemes, the performance of the proposed models was discussed addressing their effectiveness and capabilities to filter out the vulnerable set of buildings having the highest priory for detailed seismic evaluation.

2. Methodology

2.1. *Description of the building damage dataset and estimation variables*

The building dataset used in this study was generated by the collaboration of the reconnaissance teams from Middle East Technical University and Purdue University, responsible of conducting detailed post-earthquake inspections on the damaged buildings after 2003 Bingöl Earthquake (M_w=6.4) that occurred in the eastern part of Turkey (Özcebe, Ramirez, Wasti & Yakut, 2004; Sim et al., 2016). As summarized in Table 1, the building damage was defined in five discrete categories as none (N), low (L), moderate (M), severe (S) and collapse (C) damage levels, considering the observed damage patterns on the structural and the nonstructural members; and the overall integrity of the structural system. The damage data consisting of 85 reinforced concrete buildings has been compiled from the building surveys and the floor plans acquired from the database generated by the reconnaissance teams.

Table 1. Definition of building damage states.

Damage State	Description
None (N)	No observable damage
Low (L)	Hairline cracks on structural members or infill walls
Moderate (M)	Spalling of concrete, cracking of infill walls and joints, extensive flaking of plaster
Severe (S)	Localized failure in the structural system, wide and deep cracks on walls
Collapse (C)	Partial or complete collapse of the building, crushing and out-of-plane toppling of walls

As observed from the damage patterns inspected during the post-earthquake investigations, irregular configuration of the structural system, poor detailing and construction quality were specified as the main features that affected the overall performance of mid-rise reinforced concrete buildings (Yücemen, Özcebe & Pay, 2004). In this study, the prediction variables utilized as the input parameters in the classification model were determined by taking into account the effects of the total floor area and the number of stories above the ground level, the lateral strength and stiffness of the building, redundancy of the structural system as well as the building features concerning the existence of short columns, heavy overhangs, pounding effect and the soft story irregularity. With this regard, based on the comprehensive post-earthquake investigations and the observations on the typical damage patterns and the structural weaknesses of the buildings, nine input parameters were selected as the basic estimation variables to be included in the prediction models. The description of the selected variables is presented in Table 2.

Table 2. Description of the estimation variables.

Estimation variable	Description
AT	Total plan area
N	Number of stories
SSI	Soft story index
OR	Overhang ratio
NRR	Normalized redundancy ratio
NSTFI	Normalized lateral stiffness
PI	Priority index
SC	Existence of short columns
PE	Existence of pounding effect

Among the estimation variables described in Table 2., normalized redundancy ratio (NRR), normalized lateral stiffness index (NSTFI) were formerly introduced by Yücemen, Özcebe & Pay (2004) as the damage modifiers to be used in the statistical models developed for the seismic vulnerability evaluation of mid-rise reinforced concrete buildings. NSTFI was defined as a measure of lateral stiffness of the building estimated by the summation of moments of inertia values of the columns and structural walls normalized with the total floor area. The post-earthquake building inspections revealed that the continuity of the frame members played a major role in the redistribution of earthquake-induced lateral forces within the entire structure. Hence, as a measure of structural redundancy, NRR parameter was also incorporated in the classification scheme and calculated using the number of continuous frames in the orthogonal directions of the structural system.

Furthermore, priority index (PI), as proposed by Hassan & Sözen (1997), represents the overall lateral strength of the building which is obtained by normalizing the total cross-sectional area of the columns and walls with the total floor area. Due to the convenience of the required data for the calculation of priority index during field surveys, in previous studies, this index was stated as a key structural parameter to correlate with the observed damage states of the inspected buildings (Dönmez & Pujol, 2005). To represent the effect of soft story irregularity on seismic vulnerability, SSI is included as the classification variable and estimated as the ratio of heights of the first story and ground story. Moreover, overhang ratio (OR) is obtained as the ratio of the floor area of the first story (including the overhangs if exists) to the ground story. Apart from the aforementioned classification variables, in this study, the existence of short columns (SC) and pounding effects (PE) were also included in the analysis as the categorical variables of the prediction scheme.

For a preliminary analysis of the estimation variables, the pairwise scatter plot and Pearson's correlation coefficient matrix of the numerical variables are illustrated in Figure 1. The off-diagonal terms of the correlation matrix refer to the Pearson's bivariate correlations among estimation variables used in this study. Regarding the histograms of estimation variables, the distribution of the data for the total area (AT) was found to be skewed to left, while a right-skewed distribution was observed for the variable concerning the number of stories (N). Moreover, even though a weak correlation between the normalized lateral stiffness index (NLSTFI) and priority index (PI) was observed from Figure 1, the multicollinearity of the selected variables could be considered as negligible in this study.

2.2. *Model development*

As a non-parametric algorithm, decision tree has been employed for the classification of damage states of the buildings using the post-earthquake damage data from Bingöl Earthquake. As mentioned before, in recent studies, researchers have employed learning-based classification techniques to improve reliable methods for seismic vulnerability assessment based on the observed damage data gathered from post-earthquake building surveys. Taking into account the small sample size of the building dataset, decision tree algorithm, being one of the most interpretable techniques, was implemented to deal with the damage classification problem in this study.

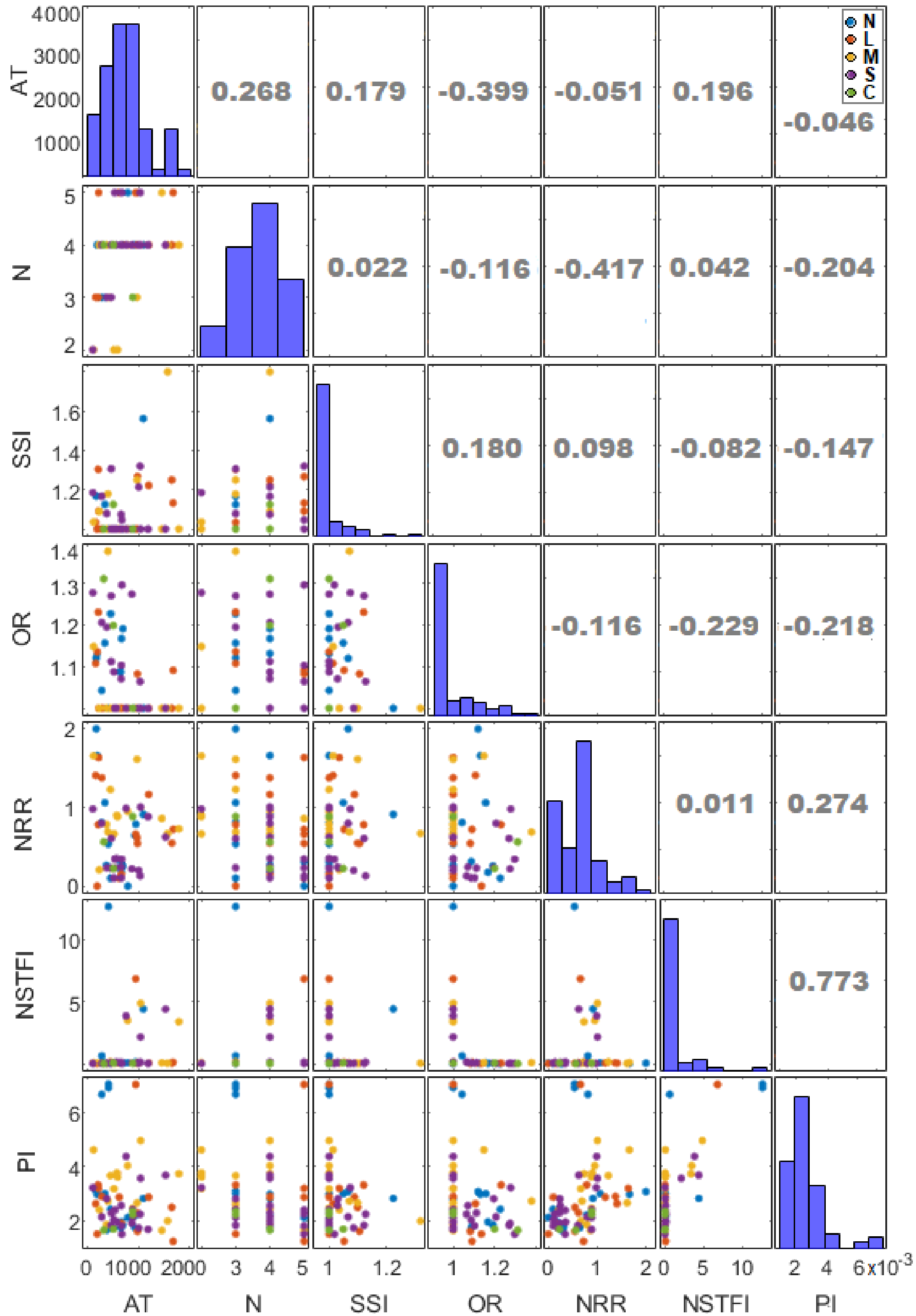


Figure 1. Distribution of the data and correlation between estimation variables.

Among the splitting criteria to obtain the best split at a given node of a decision tree, *Gini Impurity* represents the probability of misclassification of any sample from a subset of the data, in the case that the class label is randomly assigned regarding the distribution of labels within the subset. For a given ancestor node having a subset of X_t and further divided into two subsets of X_{tN} and X_{tM} (corresponding to the descendent nodes, t_N and t_M, respectively), *Gini Impurity* is determined as:

$$GINI(t) = 1 - \sum_{j=1}^{k} \left[P\left(C_j \middle| t\right)\right]^2 \qquad (1)$$

where $P\left(C_j \middle| t\right)$ represents the probability that a sample in subset of X_t exists in class C_j (Breiman et al., 1984). The estimation variable and the splitting procedure resulting with the lowest impurity measure are used for the generation of subsequent decision nodes in the classification tree. In order to generate a predictive model for the damage estimation for pre-earthquake assessment, the partitioning process is repeated recursively until the samples in the entire dataset are assigned into j categories. In the validation process of the constructed prediction models, a leave-one-out cross validation procedure has been utilized in order to overcome the limitations related to the small sample size and the imbalanced classes, especially for the collapse class region in the building dataset.

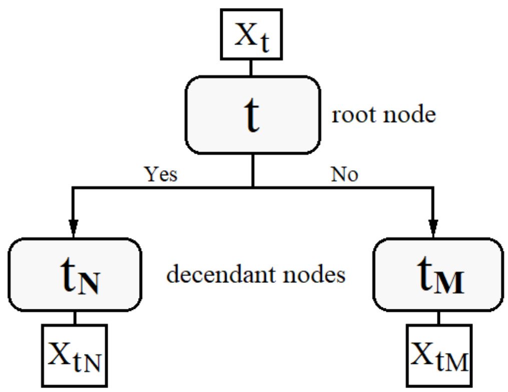


Figure 2. General structure of a decision tree.

As mentioned before, five discrete damage levels were assigned to the inspected buildings as none (N), low (L), moderate (M), severe (S) and collapse (C) depending on the observations during the post-earthquake evaluation. In this study, two different models were proposed with the implementation of classification tree algorithm (MathWorks, 2019). In the first model, the main concern was to improve a multiclass damage prediction scheme considering five damage categories as defined in the original building database. On the other hand, in the second case, an attempt has been made to introduce a vulnerability estimation scheme which is capable of filtering out the most vulnerable set of buildings that require the highest priory for detailed structural evolution. To achieve this, a tree-based binary classification model has been constructed by grouping the entire set of buildings in two subsets; the first group consisting of observations with the damage states as none, light, moderate (N, L, M) and the latter including the observations classified as severe and collapse (S, C), respectively. A similar binary classification approach has also been adopted in a previous study conducted by Tesfamariam & Liu (2010). Thus, the predictive models in the second case were denoted as life safety (LS) level assessment in this study. Finally, to compare and assess the performance measures of the multiclass and binary classification, a third model was generated by three target classes consisting of the buildings with (i) none and light damage states (N, L), (ii) moderate damage state (M) and (iii) severe and collapse damage states (S, C).

The tree-based variable importance of the nine damage indicators derived from the constructed models is illustrated in Figure 3. As expected, priority index (PI) representing the normalized lateral strength of the reinforced concrete building was ranked among the essential parameters in generating the decision tree rules for the damage predictions with five classes and life safety level assessment. It is noteworthy to mention that priority index introduced by Hassan & Sözen (1997) was found to be strongly correlated with the actual damage states of the buildings as observed during the past experience from post-earthquake structural assessments. Since the buildings designed with proper dimensioning of the lateral load-resisting members are found to perform better under the effect of seismic loads, here in this study, priority index (PI) was also determined as the key parameter in classification models.

The categorical variable for the existence of short columns (SH) was also observed to have the highest importance in the splitting process while constructing the decision-tree prediction model for LS level assessment. This finding is quite reasonable for the surveyed buildings in Bingöl inventory, since 61.77% of the buildings having severe and collapse damage states were observed to have short columns. Also, in a previous study concerning the performance of the damaged school buildings during 2003 Bingöl Earthquake, it was documented that the ground floors were collapsed due to the existence of short columns in some of these buildings (Gür et al., 2009). Thus, for the binary classification problem in this study, the short column parameter was proved to be an effective feature to discriminate the set of severely damaged and collapsed buildings from the entire building dataset. Moreover, compared with the other estimation variables, soft story index (SSI) was ranked as the least importance parameter to decide on the class region for both of the models concerning five damage states and the LS level assessment.

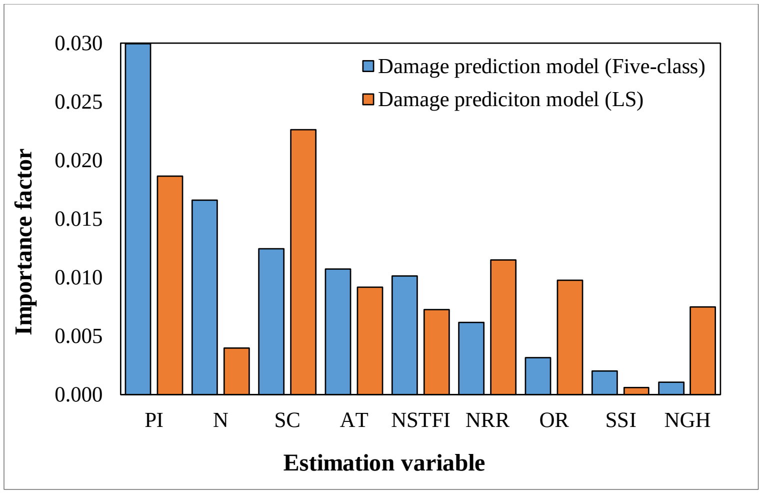


Figure 3. Importance factors of the estimation variables.

3. Results and discussion

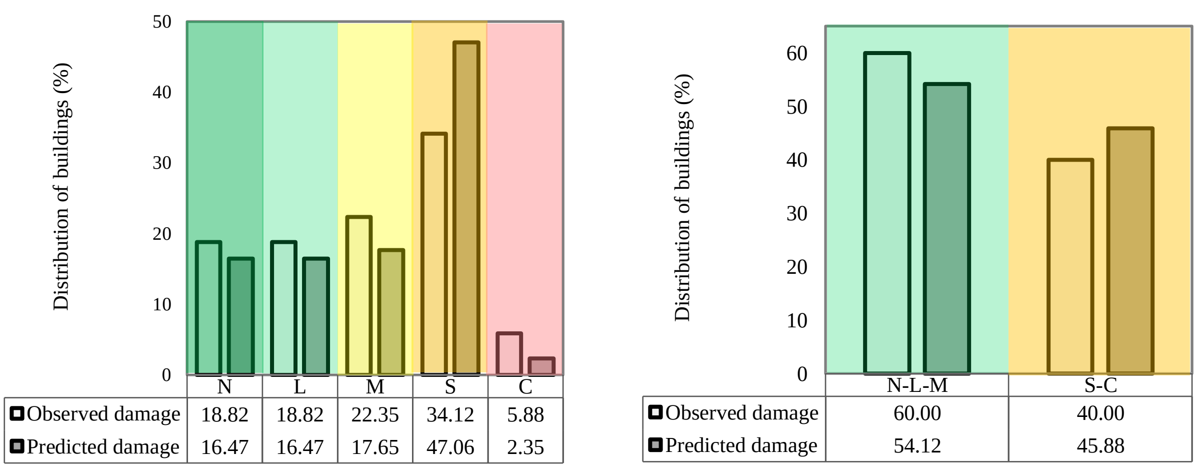
The post-earthquake damage dataset used in this study is composed of 85 reinforced concrete buildings. As mentioned before, each sample in the dataset contained nine parameters, which were used as the predictor variables along with the observed damage state of the inspected building as the response variable in damage classification. As it can be expected, regardless of the classification techniques implemented in the problem, the performance of the predictive models is mainly based on the number of correct and incorrect estimations within the entire set of observations. In this regard, the performance of the classifications was examined by comparing the damage estimations with the results of the post-earthquake assessment results in Table 3. As a measure of correctly classified observations over the entire set of building data, the accuracy results of the damage estimations acquired from the implementation of five-class, three-class and binary prediction models, were obtained as 45.88%, 58.82% and 70.59%, respectively. Moreover, to evaluate the ability of the learning algorithm to assign the correct class label for the respective damage state, sensitivity and precision results were also presented in Table 3.

As mentioned previously, the binary classification model referred to as Life Safety (LS) in this study, was proposed to identify the most critical set of buildings that might suffer severe damage or collapse having the highest priority for detailed seismic evaluation. To this end, two categories were considered for the seismic risk assessment; the first category concerning the damage states of none, light and moderate (N, L, M) and the second group is composed of damage severe and collapse (S, C) damage states. As clearly observed from the classification rates in Table 3, compared with the multiclass damage estimations encountered in this study, the proposed LS level assessment scheme achieved the highest accuracy as 70.59%, hence it was able to discriminate the cluster of most seismically prone buildings. The distribution of the buildings with respect to the actual damage states and the predicted damage categories considering the results of five-damage state and life safety level assessments are illustrated in Figure 4(a) and (b), respectively.

Table 3. Performance of the proposed models for damage estimation.

	Damage estimation (Five-class)					Damage estimation (Three-class)			Life safety assessment (Binary)	
	N	L	M	S	C	N-L	M	S-C	N-L-M	S-C
Estimations in the observed class (Correct - incorrect)	6-10	6-9	7-13	20-9	0-5	20-12	5-14	25-9	36-15	24-10
Estimations in the predicted class (Correct - incorrect)	6-7	6-8	7-8	20-20	0-3	20-14	5-7	25-14	36-10	24-15
Sensitivity (%)	38	40	35	69	0	63	26	74	71	71
Precision (%)	46	43	47	50	0	59	42	64	78	62
Total number of estimations (Correct - incorrect)	39 - 46					50 - 35			60 - 25	
Accuracy (%)	45.88					58.82			70.59	

Observing the results for multiclass damage assessment, the correct estimation rate obtained by the predictive model with five-damage states was below 50%. Also, sensitivity and precision rates regarding the five-damage state estimations revealed that the implemented scheme was unable to discriminate the buildings in the collapse region, while 68% of the buildings with severe damage could be identified correctly. Owing to the fact that the reliability of the proposed evaluation procedure strongly depends on sample size of the dataset, the limited number of surveyed buildings that exists in the database, especially for the uttermost levels of damage, is the main challenge to generate an assessment procedure with five damage states. To overcome this limitation, as an intermediate stage, the classification was also conducted by implementing the proposed model with three levels of damage assessment. For the case, the overall estimation accuracy of 58.82% has been achieved along the improvements in the results of precision and sensitivity, expectedly.

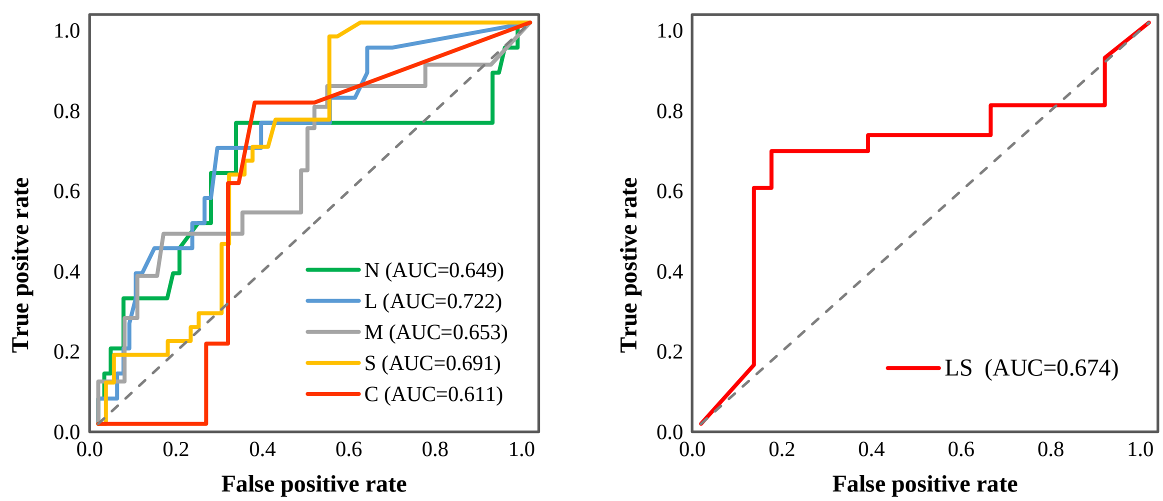


(a) (b)

Figure 4. Distribution of buildings according to the observed damage states and the predicted damage categories for (a) five-damage state estimations, (b) LS level estimations.

Along with the results of damage estimations for the buildings, the performance receiver operating characteristic (ROC) curves of the classification models are also illustrated in Figure 5. ROC curve is the graphical representation of true positive and false positive rates plotted for all possible thresholds of classification. As a measure of the effectiveness of the classifier, the area under the ROC curve (AUC) represents the model's capability in discriminating between prescribed classes. AUC score closer to unity indicate a higher performance in class separation, meaning that AUC score of unity corresponds to a perfect classification having

100% probability of detection for a particular class region. As seen in Figure 5(a), AUC scores for five-damage state assessment were found to be above 60%, while relatively higher scores could be achieved for the set of buildings having light and severe damage states as 72.2% and 69.1%, respectively. Also, for the classification scheme considering the LS level assessment, AUC score was calculated as 67.1% for the class region regarding the buildings with severe or collapse damage state. Taken together, with the use of decision tree-based classification scheme developed in this study, the model proposed for LS level assessment was able to distinguish the set of severely damaged and collapsed buildings among the entire post-earthquake building dataset, achieving a remarkably high prediction accuracy.



(a) (b)

Figure 5. ROC curves for (a) estimations with five-damage state model and (b) estimations concerning LS level assessment.

4. Conclusions and comments

Pre-earthquake seismic assessment of the existing buildings constitutes the core part of in the disaster management and earthquake mitigation activities, particularly for the seismic prone countries. Thus, in the last few decades, there is a growing interest in developing reliable techniques for the preliminary seismic risk evaluation and prioritization of the buildings that require further analysis for seismic hazard assessment. In regards to these efforts, to assess the seismic risk level of buildings at the preliminary stage, a decision tree classification approach has been adopted for generation of models to predict the potential damage to the buildings on the basis of the observed damage from Bingöl inventory.

Nine input parameters derived from the inspected features of each sample building were selected as the basic estimation variables in the prediction models. These estimation variables include total floor area (AT), number of stories (N), priority index (PI), normalized lateral stiffness index (NSTFI), normalized redundancy ratio (NRR), existence of short columns (SH), overhang ratio (OR), pounding effect (PE) and soft story irregularity (SSI). The tree-based variable importance of the nine damage indicators were obtained and it was found that priority index (PI) representing the normalized lateral strength of the reinforced concrete building was the key parameter for both of the classification models. Also, the categorical variable for the existence of short columns (SH) was observed to have the highest importance in the splitting process for the decision-tree prediction model concerning LS level assessment.

In classifying the buildings in five categories, the proposed multiclass model resulted with a poor performance in predicting the correct status of buildings in concern. Thus, the refined model concerning five damage states could not offer a robust method for vulnerability assessment due to the limitations of small sample size of the database, still can be improved by further elaborations with different databases. On the other hand, a remarkably high value of overall accuracy as 70.59% has been achieved for the predictions based on the proposed model for life safety level assessment that involve a binary classification of the damage states. Comparing the predicted states of the buildings with the results of the detailed on-site inspections, the predictive model was found to be capable of discriminating the cluster of severely damaged and collapsed buildings from the entire building database with a good accuracy. Therefore, the decision tree-based damage estimation scheme proposed in this study can be considered as an effective tool that might serve for the seismic risk prioritization of the buildings with the highest vulnerability.

Taken together, this study has revealed the great potential of utilizing machine learning techniques to improve new procedures or calibrate the existing methodologies for preliminary seismic assessment of the buildings. Since implementation of these techniques involve utilization of large datasets, further efforts are required to support post-earthquake activities for data collection from the damaged buildings and to establish reliable building damage inventories.

Funding: The author received no financial support for this research article.

Conflicts of interest: The author declares that there is no conflict of interest.

References

ATC-20 (1995). Procedures for post-earthquake safety evaluation of buildings. Redwood, CA: Applied Technology Council.

Breiman, L., Friedman, J., Stone, C. J., et al. (1984). Classification and regression trees. Boca Raton, FL: CRC Press.

Demartinos, K., & Dritsos, S. (2006). First-level pre-earthquake assessment of buildings using fuzzy logic. Earthquake Spectra, 22(4), 865–885. https://doi.org/10.1193/1.2358176

Dönmez, C., & Pujol, S. (2005). Spatial distribution of damage caused by the 1999 earthquakes in Turkey. Earthquake Spectra, 21(1), 53–69. https://doi.org/10.1193/1.1850527

Erdik, M., Sesetyan, K., Demircioglu, M., Hancilar, U., Zulfikar, C., Cakti, E., & Cagnan, Z. (2010). Rapid earthquake hazard and loss assessment for Euro-Mediterranean region. Acta Geophysica. 58(1), 855–892. https://doi.org/10.2478/s11600-010-0027-4

FEMA (2012). HAZUS-MH: Multi-hazard loss estimation methodology earthquake model. Technical manual, Federal Emergency Management Agency, National Institute of Building Science, Washington, D.C, USA.

Grünthal G. (1998). European Macroseismic Scale EMS-98. Luxembourg: European Center for Geodynamics and Seismology.

Gur, T., Pay, A. C., Ramirez, J. A., Sozen, M. A., Johnson, A. M., Irfanoglu, A., & Bobet, A. (2009). Performance of school buildings in Turkey during the 1999 Düzce and the 2003 Bingöl Earthquakes. Earthquake Spectra, 25(2), 239–256. https://doi.org/10.1193/1.3089367

Harirchian, E., & Lahmer, T. (2020). Improved rapid visual earthquake hazard safety evaluation of existing buildings using a type-2 fuzzy logic model. Applied Sciences, 10(7), 2375. https://doi.org/10.3390/app10072375

Harirchian, E., Kumari, V., Jadhav, K., Das, R. R., Rasulzade, S., & Lahmer, T. (2020). A machine learning framework for assessing seismic hazard safety of reinforced concrete buildings. Applied Sciences, 10(20), 1–18. https://doi.org/10.3390/app10207153

Harirchian, E., Lahmer, T., Kumari, V., & Jadhav, K. (2020). Application of Support Vector Machine modeling for the rapid seismic hazard safety evaluation of existing buildings. Energies, 13(13), 3340. https://doi.org/10.3390/en13133340

Hassan, A. F., & Sözen, M. A. (1997). Seismic vulnerability assessment of low-rise buildings in regions with infrequent earthquakes, ACI Structural Journal, 94(1), 31–39.

Jain, S. K., Mitra, K., Kumar, M., & Shah, M. (2010). A proposed rapid visual screening procedure for seismic evaluation of RC-frame buildings in India. Earthquake Spectra, 26(3), 709–729. https://doi.org/10.1193/1.3456711

Lagomarsino, S., & Giovinazzi, S. (2006). Macroseismic and mechanical models for the vulnerability assessment of current buildings, Bulletin of Earthquake Engineering. 4(4), 415–433. https://doi.org/10.1007/s10518-006-9024-z

Mangalathu, S., Sun, H., Nweke, C. C., Yi, Z., & Burton, H. V. (2020). Classifying earthquake damage to buildings using machine learning. Earthquake Spectra, 36(1), 183–208. https://doi.org/10.1177/8755293019878137

Matlab. (2019). Release 2019b, Mathworks Inc.

Molina, S., Lang, D. H., & Lindholm, C. D. (2010). SELENA – An open-source tool for seismic risk and loss assessment using a logic tree computation procedure. Computers & Geosciences, 36, 257–26. https://doi.org/10.1016/j.cageo.2009.07.006

Ozcebe, G., Ramirez, J., Wasti, T. S., & Yakut, A. (2004). 1 May 2003 Bingol Earthquake engineering report, http://www.seru.metu.edu.tr/archives/databases/Bingol_Database, 2004, Publication No:2004/1. (accessed on 31 January 2018)

Özhendekci, N., & Özhendekci, D. (2012). Rapid seismic vulnerability assessment of low- to mid-rise reinforced concrete buildings using Bingöl's regional data. Earthquake Spectra, 28(3), 1165–1187. https://doi.org/10.1193/1.4000065

Prasad, A. M., Iversion, L. R., & Liaw, A. (2006). Newer classification and regression tree techniques: bagging and random forest for ecological prediction. Ecosystems, 9, 181–99. https://doi.org/10.1007/s10021-005-0054-1

Rapone, D., G. Brando, E. Spacone, & De Matteis ,G. (2018). Seismic vulnerability assessment of historic centers: Description of a predictive method and application to the case study of Scanno (Abruzzi, Italy). International Journal of Architectural Heritage, 12(7–8), 1171–1195. doi:10.1080/15583058.2018.1503373.

Ródenas, J. L., García-Ayllón, S., & Tomás, A. (2018). Estimation of the buildings seismic vulnerability: A methodological proposal for planning Ante-Earthquake scenarios in urban areas. Applied Sciences, 8(7), 1208. https://doi.org/10.3390/app8071208

Sim, C., Song, C., Skok, N.R., Irfanoglu, A., Pujol, S., & Sozen, M. (2016). Database of low-rise reinforced concrete buildings with earthquake damage. https://datacenterhub.org/deedsdv/publications/view/454 (accessed on 10 November 2018)

Sucuoğlu, H., Yazgan, U., & Yakut, A. (2007). A screening procedure for seismic risk assessment in urban building stocks. Earthquake Spectra, 23(2), 441–458. https://doi.org/10.1193/1.2720931

Şen, Z. (2010). Rapid visual earthquake hazard evaluation of existing buildings by fuzzy logic modeling. Expert Systems with Applications, 37(8), 5653–5660. https://doi.org/10.1016/j.eswa.2010.02.046

Tesfamariam, S., & Saatcioglu, M. (2008). Risk-based seismic evaluation of reinforced concrete buildings. Earthquake Spectra, 24(3), 795–821. https://doi.org/10.1193/1.2952767

Tesfamariam, S., & Liu, Z. (2010). Earthquake induced damage classification for reinforced concrete buildings. Structural Safety, 32(2), 154–164. https://doi.org/10.1016/j.strusafe.2009.10.002

Tesfamariam, S., & Saatcioglu, M. (2010). Seismic vulnerability assessment of reinforced concrete buildings using hierarchical fuzzy rule base modeling. Earthquake Spectra, 26(1), 235–256. https://doi.org/10.1193/1.3280115

Tomás, A., Ródenas, J. L., & García-Ayllón, S. (2017). Proposal for new values of behaviour modifiers for seismic vulnerability evaluation of reinforced concrete buildings applied to Lorca (Spain) using damage data from the 2011 Earthquake. Bulletin of Earthquake Engineering. 15(9), 3943–3962. https://doi.org/10.1007/s10518-017-0100-3

Yıldızlar, B., Akcay, C., & Öztorun, N. K. (2018). A rapid analysis method for determining current status of existing buildings: A conceptual framework. Revista de La Construccion, 17(2), 267–278. https://doi.org/10.7764/RDLC.17.2.267

Yücemen, M. S., Özcebe, G., & Pay, A. C. (2004). Prediction of potential damage due to severe earthquakes. Structural Safety, 26(3), 349–366. https://doi.org/10.1016/j.strusafe.2003.09.002