ARTIFICIAL NEURAL NETWORK BASED STRUCTURAL SEISMIC DAMAGE DETECTION FROM MONITORING ACCELERATION DATA

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Abstract

Fast structural damage detection is one of the most important mission for timely earlier earthquake resilience in seismic prone area. The conventional ways of damage investigation conducted manually after main shock are complex, labor intense, time consuming and tedious. Hence, as an alternative to the prior methods, studies with non-parametric approach that uses machine learning techniques has been an emerging topic in the field of research in Earthquake Engineering.

In this study, the feasibility and performance of using Artificial Neural Network (ANN) based algorithm using acceleration for the damage recognition with the help of numerical models has been studied. Different lumped mass models (SDOF and MDOF) are considered for non-linear analysis and are numerically simulated to get the structural responses under 18 different designed earthquakes. In this neural network, the structural acceleration and calculated displacement are used in the input layer and then the different damage label (damaged or undamaged) would be obtained from the output layer. Non-linear seismic simulation has been conducted to generate database, which has been used for training the network and classifying the input data into two output classes. Two different layers of networks are used in the classification method. In first part of the study, the network is trained only using the acceleration and calculated displacement from SDOF model, and tested with the test data from the same structural model. Moreover, in the second part of the study, both acceleration and displacement signals from SDOF are used in the training the network and test data sets that are generated using 3DOF and 5DOF models were used to test the network. The classification result shows very high accuracy up to 95.5% and 88.0% in the first case and later case respectively. Further, the damage labels are divided into five different categories and used in the training and testing the Neural Network. Overall result shows good classification accuracy about 83.8% in almost all categories of damage levels with one exception. Establishment of a universal framework for detecting damage on structures based on a trained network with certain structural parameters has been explored. ANN algorithm trained by using data from simple model has been used in classification of labelled data from complex models. Feasibility and performance of such method has been presented in different cases. Also, limitation and need of further research work in this method has also been discussed.

Keywords: Artificial Neural Network; Algorithm; Damage Detection; Non-Linear Analysis

1. Introduction

Bridges are one of the most important civil infrastructures in transportation network in the world. This part of infrastructure has become the backbone of economic activities to the areas it connects, thus, has high importance in socio-economic development. In engineering point of view, these structures have always been a challenge for resilient design and continuous serviceability due to its exposure to damage and deterioration due to traffic loading and seismic activities during its service life.

It is evident that numbers of road bridges are damaged by the earthquake in the past (Tohoku Earthquake, 2011, and Kobe Earthquake,1995) disrupted the transportation network which has direct impact on emergency response and long-term impact on the regional economy [1]. The inspection surveyed were carried out on foot at the sites of each of the surveyed bridges in which less number bridges were only surveyed in one occasion. This signifies that it takes longer time to check the damages in the bridge by visual inspection. One of the most common method of damage detection in structures are through visual inspections by the experts. Experts must be in site location to visually scan through all the detail parts of the structures, which could be risky for their life, when they are near or inside the structures which may have been badly damaged and could collapse at any unknown time. Thus, experts use different kinds of vehicles or machines to assist the visual inspections, which may also cause disruption to the smooth flow of the traffic in the road network. Such visual inspection can only detect the cracks, spalling of surface materials, staining, surface blemishes, weathering, seepage marks, corrosion, color changes and staining. This method is very basic for the routinely repair and maintenance and requires further detailed investigation for the quantitative damage recognition [2]. This conventional method has other challenges such as high cost, limited number of experts available, lack of uniform standard for quantitative evaluation and higher risk for experts while checking. Such visual inspection can recognize the outer damage of the structure and fails to recognize the internal damages. Thus, different types of sensors are installed in the bridge structures for the continuous monitoring as well as to study about the behavior of such structure during the seismic activities. The data collected through the sensors are then processed and analyzed for the damage recognition.

Number of sensors that are installed in the different parts of the structures for detailed investigation records the structural responses under different types of loading. One day measurement or continuous monitoring is carried out depending on the nature and need of the investigation. Long-term or continuous monitoring may cost lots of human resources, longer time and might be costly due to requirement of high number of sensors. Such sensors installed at different parts of the structures gathers information of vibrations due to daily traffic loads and even earthquakes. Information or data can be collected manually or through wireless technology using internet. Once the data are collected, they are pre-processed for further analysis. There are many parametric methods that includes structural parameters like frequency, Time-period, damping ratio, modal strain energy, mode shapes etc. [3, 4, 5]. However, these approaches are labor intensive, takes longer time for computation and costly. In other hand, some of the methods may also require complex Finite Element Model (FEM) and are complicated and tedious resulting in longer time for the analysis and evaluating the damage state. There are a lot of research works conducted by using the low-cost sensors for structural monitoring. Micro-Electro-Mechanical-Systems (MEMS) technology based low-cost sensors applied for Wireless Sensor Networks (WSN) in structural monitoring are evident in many researches [6, 7, 8]. Such method needed filtering unit on board for digital data processing, which swept frequencies and the accelerometer response was limited to certain range, which might result to recorded acceleration amplitude reflect false state of damage level in the structure.

Besides these many methods, engineers also have been using other techniques such as, artificial neural networks [9, 10, 11]. In recent decades, researcher has been extensively researching about the non-parametric approaches which doesn't need accurate and complex finite element modeling of the structures as in previous methods. Artificial Neural networks (ANN) have been an increasing interest to predict and estimate the damage in the structures [12, 13].

In 1995, the feasibility of using ANN with system identification to detect the damage existence and to identify the characteristics of damage in delaminated beam structures [14]. Various types of damage patterns according to the location and severity of the damage were introduced as pattern classes in the input layer of the neural network. The feasibility study of applying an ANN trained with natural frequency data to identify the damage in scaled down steel bridge girder [15]. Prediction of the damage level in bridge seismic monitoring system using ANN with different categories of damage levels, as an indication of bridge damage after the occurrence of seismic activity has been studied [16]. This study used the value of Peak Ground Acceleration (PGA) from the sensors located at the top of the pier in the FEM as the input for the NN. Finite Element Analysis was carried out to get the structural response with the excitation of earthquake with PGA of 0.1g. It was also mentioned the merit of using ANN that the damage level relationship is not needed between the output and input. Studies has also been carried out with experiments using a simple truss bridge and a real truss bridge structures for a neural network-based system identification approach to estimate the damage percentage [17]. Sub structural techniques was used to reduce the number of unknown parameters in case of a real truss structure and found out to be very efficient. The study also summarized that the location and severity of damages in the joints of truss bridges can be found with good precision.

Most of the research that has been carried out in past uses finite element models or experimental models to generate the training data and uses modal parameters like frequency and mode shapes as input. One of the limitations of these studies is that the trained model in respective study was used for damaged detection in same structural model and didn't extend to other types of structures. Also, these method uses simulation finite element models which could be time consuming to build and experimental works, of course, add up the time and funding to execute.

This paper addresses the above-mentioned limitations using Artificial Neural Network (ANN) as a feature extractor and classifier to detect the damages in the structure. The response acceleration and calculated displacement data has been used as input to output damage and undamaged state of the structure.

2. Numerical Simulation and Data Acquisition

Two different models (simple SDOF and a 3DOF bridge model) with damping ratio of 5% are considered in this study. Fig.1(a) and (b) represents the simple SDOF and 3DOF lumped mass bridge model. Simple one degree of freedom system with point mass (m) and stiffness (k) has been considered for the generation of simulated response data for the training of the Neural Network. A single pier transverse direction bridge model has been considered as bridge model, each mass representing mass of bridge deck, pier and piles respectively. This model could also be used to represent the lumped mass model of 3-storeyed building.

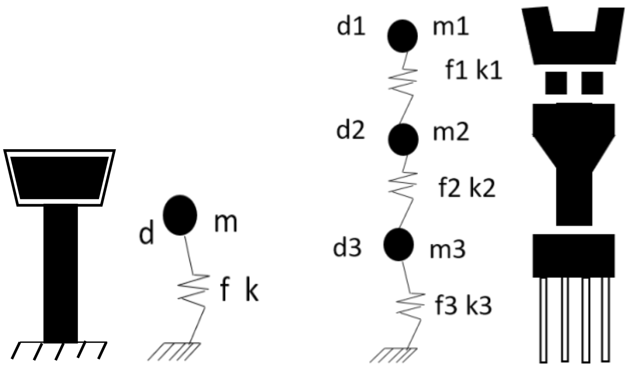


Fig. 1 – Lump Mass Models

The input data (acceleration and displacement) are generated from Non-linear Analysis using 18 different designed earthquakes (Level 1 and Level 2) to excite these models. Lumped mass model with the structural parameters as in the Table 1 are considered. The value of stiffness ratio (α) for all the considered models ranges from 0.1 to 0.6, yield acceleration value (a_y) from 0.2 to 1.2 m/s2. However, during the simulation, these values are chosen randomly to consider different kinds of structures with equivalent properties of steel or concrete with short or tall pier and short span or long span. Structure with time-period ranging from 0.3 to 2 secs are considered in this study. Unit mass has been considered for all the point mass for simplification of the calculation. Stiffness values are calculated depending on the time-period for both models. All the models are considered as a bilinear model in the analysis.

Table 1 – Non-Linear Structural Parameter Settings

Parameters	SDOF	Bridge Model	Remarks
Time-Period (T)	0.3~2 secs	0.5~2 secs	Eigen Value Analysis
Stiffness (k)	$\left(\frac{2\pi}{T}\right)^2 * m$	$\left(\frac{2\pi}{T}\right)^2 * m$	Depends on value of T (N/m)
Mass (m)	1	1	Unit mass (kg)
Stiffness Ratio (α)	0.1~0.6	0.1~0.6	
Yield acceleration (ay)	0.2~1.2	0.2~1.2	

The basic concept of displacement calculation from seismic structural response is based on the equation of motion as in Eq. (1)

$$ma + cv + kd = ma_g \tag{1}$$

where, ma_g, ma, cv and kd are the acceleration due to ground motion, inertial force, damping force and spring force respectively. Newmark's beta with Incremental-step has been carried out to get the structural responses under seismic excitation. At any time of point (n+1) Δt, the equation of motion can be expressed like following;

$$ma_{n+1} + cv_{n+1} + kd_{n+1} = ma_{g,n+1} \tag{2}$$

The acceleration data ({a}= {a1 a2 a3}) generated from the numerical simulation are double integrated to get the displacement ({d}= {d1 d2 d3}) at the respective locations using the Eq. (3), also the ground displacement (dg) is also calculated by integrating the ground wave motion using Eq. (4). The deformation at ith spring are calculated using Eq. (5) and Eq. (6). Then, the mass normalized spring force (f) in terms of acceleration (a) are presented as in Eq. (7) and Eq. (8).

$$\{d\} = \iint \{a\} dt^2 \tag{3}$$

$$dg = \iint a_g dt^2 \tag{4}$$

$$u_1 = d_1 \text{-} d_g \tag{5}$$

$$\mathrm{u_i} = \mathrm{d_i}\text{-}\mathrm{d_{i\text{-}1}}, \mathrm{i} > 1 \tag{6}$$

$$\mathrm{f_n} = \mathrm{r_n}, \mathrm{r} = \mathrm{ma} \tag{7}$$

$$\mathrm{f_i} = \mathrm{a_i}\text{-}\mathrm{r_{i+1}}, \mathrm{i} < \mathrm{n} \tag{8}$$

Here ai is the acceleration measured on the i degree of freedom. mi are simplified to use the unit mass 1 in this study, assuming the mass are evenly distributed in each floor of building or structural models.For each spring, ith input data for damage detection is of 3 second spring deformation data {ui} = {ui,1 ~ ui,300} and 3 second normalized spring force {fi}={fi,1 ~ fi,300}. As sampling rate is 100Hz, the number of deformation (ui) and force (fi) are of 300 each.

$$x(1 \sim 300) = \{u_i\}/\max(|\{u_i\}|) \tag{9}$$

$$x(301 \sim 600) = \{f_i\}/\max(|\{f_i\}|) \tag{10}$$

where, | | is the function of return absolute value.

Nonlinearity of the structure can be measured in terms of ductility, which is the ratio of maximum displacement to the yield displacement. The curvature of the ductility depends on the material properties and cross-section of the structure. Thus, displacement ductility has been calculated by the Eq. (11).

$$\mu = \frac{D_{max}}{d_y} \tag{11}$$

where, μ is the ductility, D_{max} the maximum displacement and d_y is the yield displacement.

Same equation has been applied here to classify the damage and undamaged structure. Damaged class was determined with simple condition; when the ratio of maximum value of response displacement (D_{max}) the Yield displacement (d_y) is greater than 1 and undamaged class, if the ratio is less than 1 as shown in the Eq. (12) and Eq. (13). The visual interpretation of the same can be seen in Fig. (2).

$$\mu = \frac{D_{max}}{d_y} > 1 \quad (Damaged) \tag{12}$$

$$\mu = \frac{D_{max}}{d_y} < 1 \quad (Undamaged) \tag{13}$$

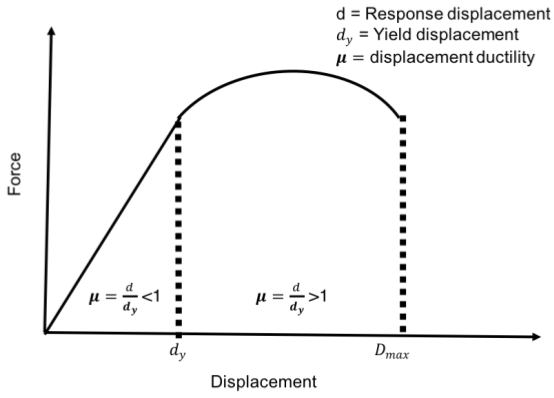


Fig. 2 – Force-Displacement Curve.

Simulated data has been processed for the data normalization to reduce data redundancy and improve the data integrity. Another merit for this process is that it reduces the computational time during training and classification. Simple method of data normalization has been carried out in this study. Min-Max scaling method has been adopted to get the normalized data in the range of 0 to 1. Both response acceleration and calculated displacement equal to the length of the earthquake waves during the simulation are normalized to the length of 300 (150 data from maximum values at both ends) in each case. Fig. 3 shows a sample of a normalized acceleration data. Similar normalized data for training and test the Neural Network has been presented in the later chapter.

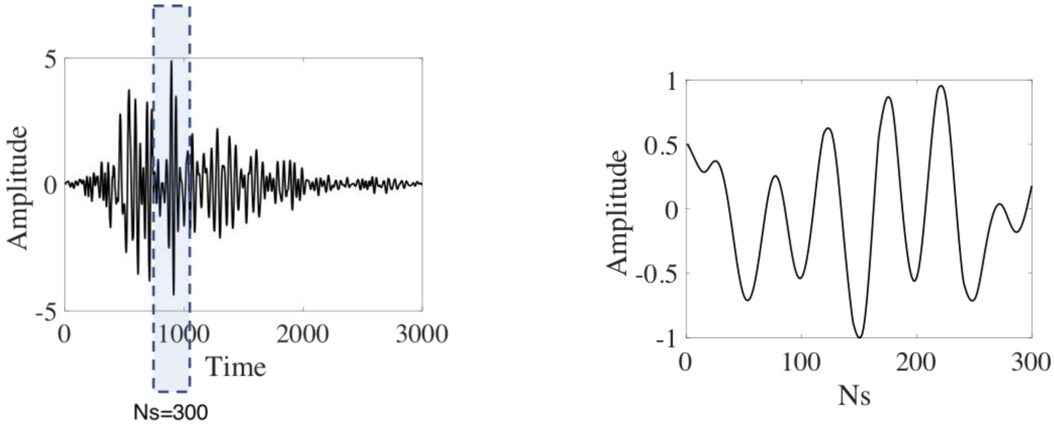


Fig. 3 – Data Normalization

Since, the input data as well as test data are labelled before training and testing of the trained network, these neural networks are also referred as supervised learning. These data are labelled into damaged and undamaged class. The response data from SDOF are used for the training the neural networks. 3 different size of training data set of 5000, 10000 and 20000 (later called as Data-1, Data-2 and Data-3 resp.) are generated from SDOF model by non-linear analysis as discussed in previous chapters. 20% of the training data which are not included in the training are used as test data and the test data of size 100 (the number of independent waveforms each of length 3 secs sampled at 100 Hz), Test Data-1 from bridge model are used for the testing the classification. The data types for both cases can be seen in the tabulated form in Table 2. The resulting percentage of accuracy from two types of network used in this study shows the reliability, accuracy and robustness of this approached method.

Table 2 – Types of Data Sets.

Model	**Training Data**	**Validation Data**	**Test Data**	**Model**
SDOF	Data-1 Data-2 Data-3	Val. Data	Test Data-1	Bridge Model

3. Neural Network Based Damage Detection

3.1 2-Layer Neural Network (ANN-1)

ANN-1 is a multi-layer feedforward network (one input layer, one hidden layer and one output layer), with a sigmoid transfer function in a hidden layer, and a Softmax transfer function in the output layer. In this neural network, the structure response (displacement and acceleration) were used in the input layer and then the damage label (damaged or undamaged) would be obtained from the output layer. The operation mechanism of ANN can also be referred as supervised learning. Inputs; acceleration and displacement data were normalized to 300 number each, so the input vector of length 600 was fed to 100 hidden layers of the neural network with sigmoid transfer function and then passed through softmax classifier to output the probability of 2 target classes. Fig. 4 shows the view of 2-Layers Neural Network used in this study.

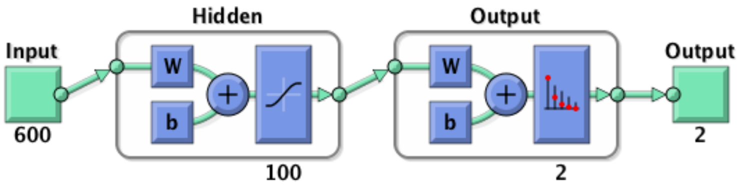


Fig. 4 – View of ANN-1

3.2 3-Layer Neural Network (ANN-2)

The three-different layers (autoencoder-1, autoencoder-2, and softmax), were stacked together as shown in Fig 5 to form ANN-2. The 600-dimension input was reduced to 100-dimension in first encoder layer and fed forward to second encoder of 50 dimension for feature extraction and then softmax classifier was used in output layer to output 2 predicted classes.

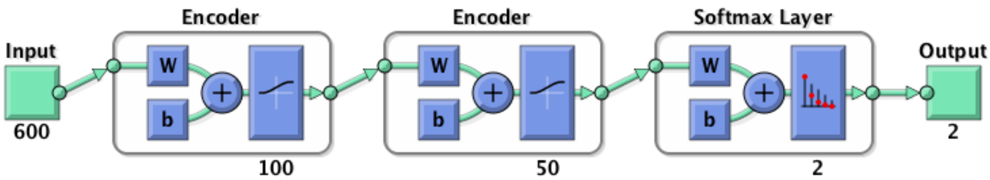


Fig. 5 – View of ANN-2

An autoencoder is a feedforward, unsupervised neural network which represents the inputs with reduced dimension. It learns the correlation in the input data with a smaller number of neurons in hidden layer than number of inputs. The features were generated using the encoder. Then, a decoder reconstructs the input size from the hidden layer. First autoencoder comprises of an encoder followed by a decoder. The encoder guides an input data to the hidden layer and decoder reverse this mapping to reconstruct the original input. An autoencoder replicates its input at its output, thus, the size of the input (600) was same as the size of the output (600) but the size of hidden layer in encoder was 100 neurons. Both acceleration and displacement signal were of 3 secs each sampled at 100 Hz. The number of neurons in the hidden layer was equal to 100, which was less than that the size of the input. The 100-dimensional output from the hidden layer of the autoencoder is a compressed version of the input, which summarizes its response to the features. Initially, the weights were random before training, therefore, the results from the training were different each time. The influences of these regularizers was controlled by setting various parameters like; L2WeightRegularization, Sparsity Regularization, and Sparsity Proportion. Following values as shown in Table 3, were taken in this study. The Graphic Processing Unit (GPU) was used for the training or testing the classification problem of this study. The use of GPU would shorten the computational time, but it could be costly.

Table 3 – Values of different parameters in an autoencoder.

S. N	Parameters	Value
1	MaxEpochs	500
2	L2WeightRegularization	0.0001
3	Sparsity Regularization	0.0001
4	Sparsity Proportion	0.1
5	UseGPU	False

Similarly, the second autoencoder was also trained in a similar way as the first autoencoder. The features that has been generated from the first autoencoder as the training data was used in the second one. Here, the size of the hidden layer was decreased to 50, so that second autoencoder learns smaller representation of the input data. The values for regularization was considered as same in first encoder as shown in Table 3.

The original vectors in the training data had 600 dimensions, which was reduced to 100 dimensions after passing them through the first encoder. After using the second encoder, this was reduced again to 50 dimensions. The final layer was trained to classify these 50-dimensional vectors into two classes (damaged and undamaged) through softmax classifier.

4. System Performance

Neural Network was trained using three different size of training data set (Data-1, Data-2 and Data-3) of SDOF. Normalization of data was carried out and then labelled as well. The normalized acceleration vs. displacement data that has been used in training the model can be visualized as shown in Fig. 6 and Fig. 7 shows the normalized test data from the bridge model.

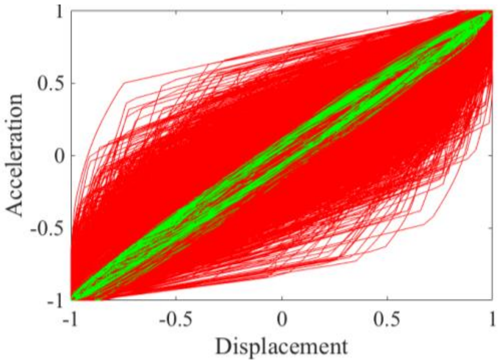


Fig. 6 – Normalized test data from SDOF Model

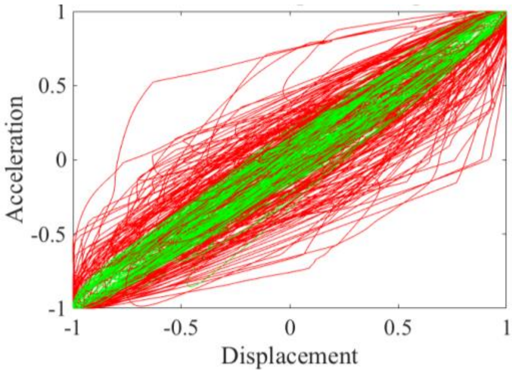
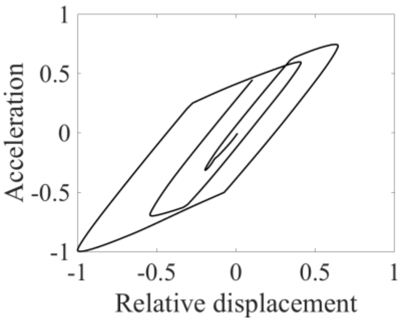


Fig. 7 – Normalized test data from Bridge Model



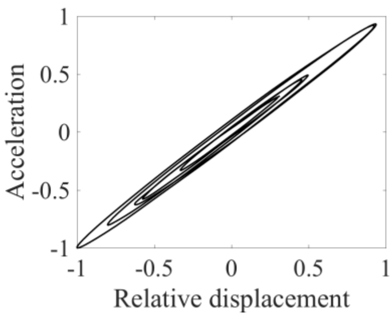


Fig. 7 – Damaged and Undamaged acceleration-displacement data

Fig. 7 shows the representative of damaged and undamaged acceleration displacement data used in the training as well as test data used in this study. Visually, we can see the clear difference between the plots of damaged and undamaged cases. The Neural Network was trained using three different size of dataset; Data-1, Data-2, and Data-3 from SDOF. Test data from bridge model were used in two different classification; ANN-1 (2-Layers Network) and ANN-2 (3-Layers Network).

Table 4 – Classification accuracy in different Neural Networks.

Models	**Classification Network**					
	ANN-1			ANN-2		
	Data-1	Data-2	Data-3	Data-1	Data-2	Data-3
SDOF	84.80%	89.90%	93.00%	90.60%	94.70%	95.50%
Bridge Model	81.00 %	82.00%	84.30%	83.00%	86.70%	88.00%

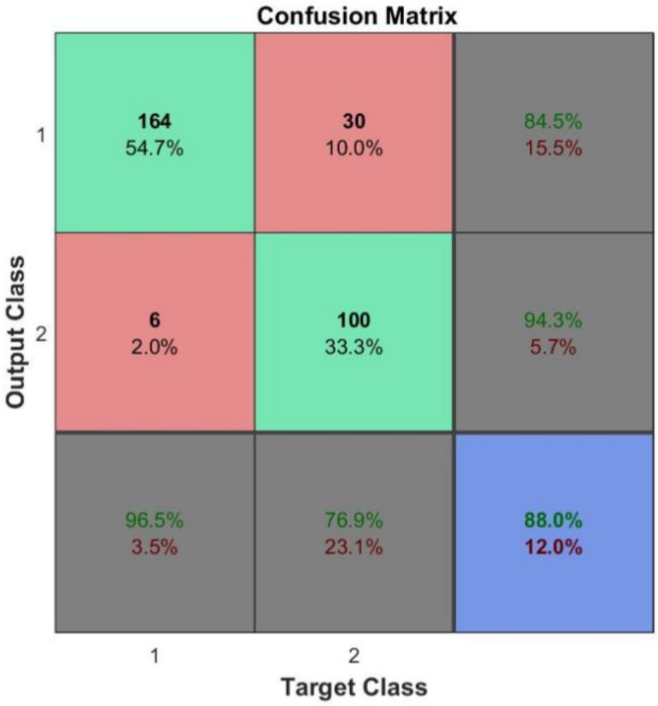


Fig. 8 – Classification result of Bridge Model test data in Data-3 training.

When the validation data (20% of training data size), was used for the testing of the trained Neural Network, the results showed very high accuracy up to 95%. The results can be seen in the tabulated form in Table 3 and a sample of classification result in form of confusion matrix in Fig. 8. The accuracy got better with increase in the size of the training data set. ANN-1 showed results increasing from 84.8% to 93% and ANN-2 showed results increasing from 90.6% to 95.5%. The difference between the accuracy in two networks can also be seen in the table. The deeper network with Autoencoder shows higher accuracy than the simple 2-layers network. These results show that approach method can classify or detect the damage from the structural response data. Further, test data from Model A was used to test the same trained Neural Network and found out that the same Neural Network can successfully classify the data with classification accuracy above 80% in all the cases. The results got better with deeper network and larger training data size as in prior. The accuracy was calculated from the confusion matrix with the Eq. (12).

$$accuracy = \frac{t_p + t_n}{t_p + t_n + f_p + f_n} \tag{12}$$

Where, t_p = true positive, t_n = true negative, f_p = false positive and f_p = false positive.

Further, same Data-3 from SDOF model, with 6 different damage labels namely; DL0, DL1, DL2, DL3, DL4, DL5 and DL6 was used for the classification performance of the Neural Network. The different levels were determined with different range of ductility values. The training data with uneven samples of different damage labels were used to classify the data of total 4000 (Test Data) as shown in the Table 5.

Table 5 – Classification accuracy with 6 damage labels.

S.N	DL	$\mu = d/dy$	Data-4	Test Data
1	DL0	$\mu < 1$	4504	760
2	DL1	$1 < \mu < 2$	6111	1024
3	DL2	$2 < \mu < 3$	3776	584
4	DL3	$3 < \mu < 4$	2303	445
5	DL4	$4 < \mu < 5$	1407	226
6	DL5	$\mu > 5$	5899	961

The confusion matrix in Fig. 9 shows overall accuracy of about 84%, which is also pretty much good result in all the damage label with one exception for DL4.

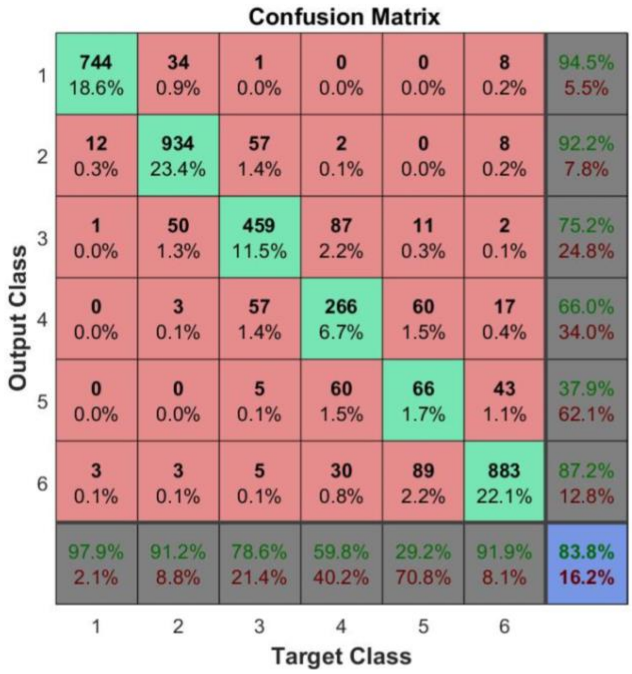


Fig. 9 – Classification result for 6-damage labels.

This classification has only been carried with the training data from SDOF only. Further work need to be carried for testing the neural network using test data from other models.

5. Limitation and Conclusion

Numerical simulation was carried out to generate the structural response data that would cover the range of damage state of structure due to ground excitation. Random selection of non-linear parameter and different scale of input earthquake generated wide range of response. Such response acceleration and respective calculated displacement data was used for the training of the neural network from simple SDOF model representing a bridge. The non-linear dynamic analysis used in this study was found out to be unstable for the structures with higher frequencies. Limited number of iterations for the correction of response values could be one of the reasons for the instability seen in the analysis. This study limits only to the lower frequency ranges. So, further study is needed to explore about the reason for the instability of the system. The numerical models were considered lumped mass and the damage labelling to the structure was implemented in very simple manner for easy calculations and can form a basis for future research work in similar study. More complex models and real values for the structural parameters can also be used for more accurate response as in the real structures. Simulated data was used, thus, the method studied has yet to be verified with the real structural response data gathered in the real structures. Also, not having a model of the structure and different damage scenarios prevented from being able to physically interpret the cause of the behavior in the structure.

From the above results, it can be concluded that the performance of the system also depended on the number of data used in the training of the neural network. The results got better when the neural network is trained with larger training dataset. Neural network architecture also showed important role in the overall classification accuracy. Since the weights are initialized randomly during the training process, the classification results showed varying results during testing using the same neural network and test data set. Classification accuracy of this method was carried out using a constant value of learning rate in neural network training and exploration in the effect of tuning this hyper parameter is yet to be explored.

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