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ANN Base Structural Failure Prediction Of Multi-Storey RC Buildings

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Abstract – Structural defect prediction in RC buildings, especially multi-storied buildings has long been an active area of research among structural engineers. While several standards pertaining to different geological conditions are available and are adhered to while structural design, yet it has been seen that due to external factors and non-compliance with exact standards, there exists a chance of building failure. Conventional techniques rely on pre-defined standards, but due to minute details and random nature of values, it is difficult to find regular relations or patterns among them. In this paper, standardized RC building data has been used to train an artificial neural network and subsequently is has been used to test the neural network model for predicting building failure. A total number of fifty RC buildings have been utilized for data mining. As a standard convention, 80% of the data has been used for training and remaining 20% data has been used for testing and validation. It has been found that the designed ANN structure predicts with approximately 98.51% accuracy which can be attributed to the efficacy of the Bayesian Regularization algorithm used for employing back propagation in the designed ANN structure. It may possible that the present research or proposed methodology using ANN technique may provide a guideline to detect defect or failure prediction in structural RC buildings with high accuracy.

***Key Words*:** *Structural failure prediction, artificial neural networks, back propagation, Scaled conjugate gradient, mean square error, accuracy*

1.INTRODUCTION

This Structural failure prediction has always remained a challenging aspect of structural design. The issue becomes even more daunting in case of multi storey RC buildings. With the advancements in structural design, the need for prediction of failure needs to be addressed. Conventionally, statistical methods were used for failure prediction, but with increasing complexities in designs and relevant parameters, predicting failure with high accuracy becomes extremely tedious and difficult. [4] Hence researchers started investigating alternatives for high accuracy prediction.[7] As it turned out, using Artificial Intelligence for such a data mining, analysis and prediction mechanism came forth as a promising technique for the same. The flow of such a data mining and analysis paradigm is shown below in Figure 1.

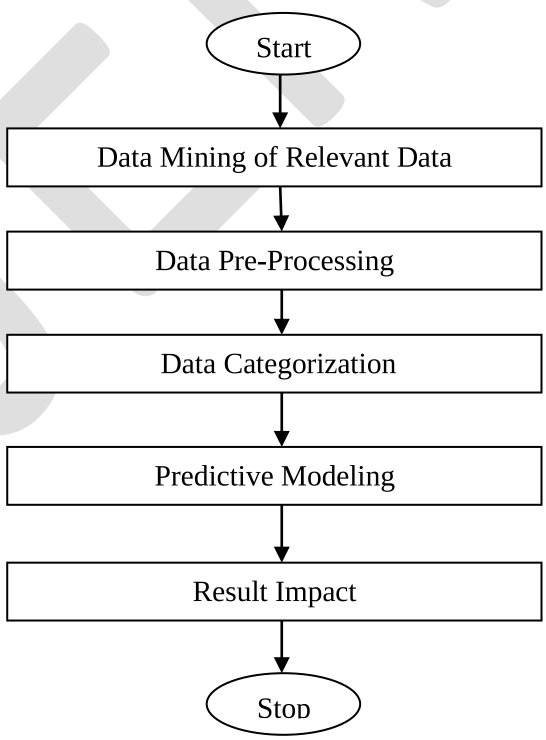

Fig-1. Basic data mining and predictive modeling approach

One of the techniques that are used these days, the use of artificial intelligence to accomplish tasks which are complex but need human intervention. Data mining is an application of knowledge process within which skilled patterns and knowledge is extracted. [3] The extracted information is subsequently used in real time applications for creating decisions. Analyzing enormous amounts of mined data can be daunting for mechanisms depending completely on human intervention. Hence it's is being thought for that such applications can be better handled using artificial intelligence. The practical structure that is used to implement artificial intelligence is called an artificial neural network (ANN). A brief introduction of ANN is discussed in following subsequent section.

2. ARTIFICIAL NEURAL NETWORKS

An artificial neural network tries to emulate the human brain which is a natural neural network. Neural networks are gaining immense importance due to the fact that they can be used to implement artificial intelligence. The artificial neural network paradigm is similar to the human brain in the following ways such as it has a highly non-linear structure, it can accept data in a parallel manner and it can learn and adapt synonymous with the human brain's nature. [3] The non linear structure augments the fact that the neural network doesn't treat all inputs similarly which is a fundamental attribute of the neural network. This helps in changing or updating the weights of the ANN depending upon the importance of a particular input in its capability of affect the output. Accepting data in parallel helps in parallel processing and high speed of the ANN resembling the nature of the human brain in accepting data in parallel form various body parts. The mathematical counterpart of the biological model for a neural network is presented in the Fig-2.

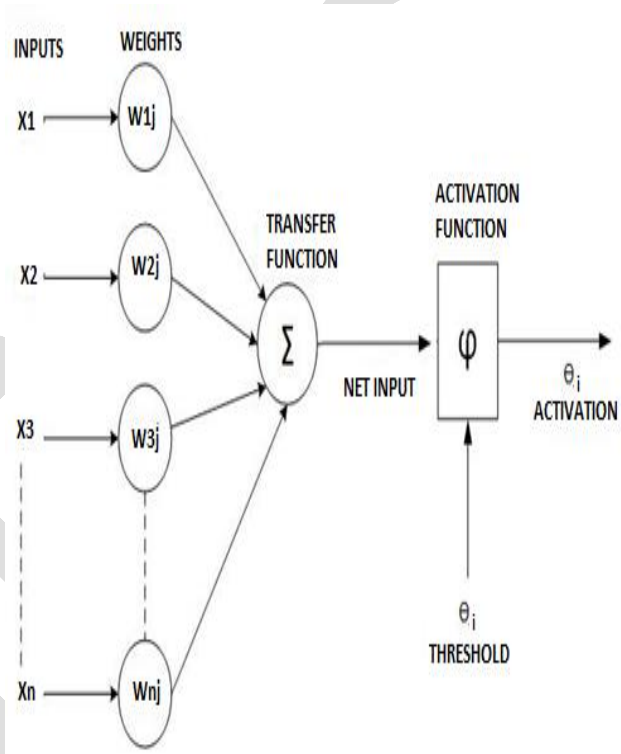

Fig-2 Mathematical counterpart of the biological model for a neural network

The fact that the neural network can accept and process data in parallel ensures high speed of operation of the neural network. The learning and adapting capability of the neural network ensures the fact that data can be processed at a high speed. These three attributes make the artificial neural network perform tasks generally needing human intervention. The output of and ANN can be represented by Equation 1:

$$y = \sum_{i=1}^{n} x_i \ . w_i \ + \phi \qquad (1)$$

Where,
Y denotes output of the ANN,
X denotes the inputs to the ANN,
w denotes the weights of the ANN and
ϕ denotes the bias.
The weights keep changing or adapting as the neural network keeps learning or training through the epochs or iterations.
The bias is the additive logic needed to find the relation in the training input data.

2.1 Back Propagation in ANN

Back propagation in ANN corresponds to the ANN structures where predictive errors are fed back to the neural network so as to make the ANN learn better and faster. The most important attribute is the ANN is the capability to learn and adapt. It can be thought of a mechanism in which the weights are updated in such a way that errors in predictive classification keep reducing in successive iterations. This resembles the human attribute of improving in successive steps. Back propagation is found to reduce errors much faster than feed forward neural networks.[12]While various types of neural networks can be designed, yet one of the most effective forms of neural networks is the mechanism of back propagation in which the errors of prediction are used to update the weights of the existing neural networks with an aim of reducing the errors in subsequent predictions. From Fig-3, it is clear that after the initiation of training initial values of weights are to be assumed. Then input data is processed in sets. After all sets of input data are processed, then error is calculated.[1] If the error is within tolerant range, then network weights are saved and training is ended. If the error is not in the range of tolerance range, then check for number of epochs. If epochs exceeded maximum value, then show failure massage and end training else retrain network until required results are obtained.

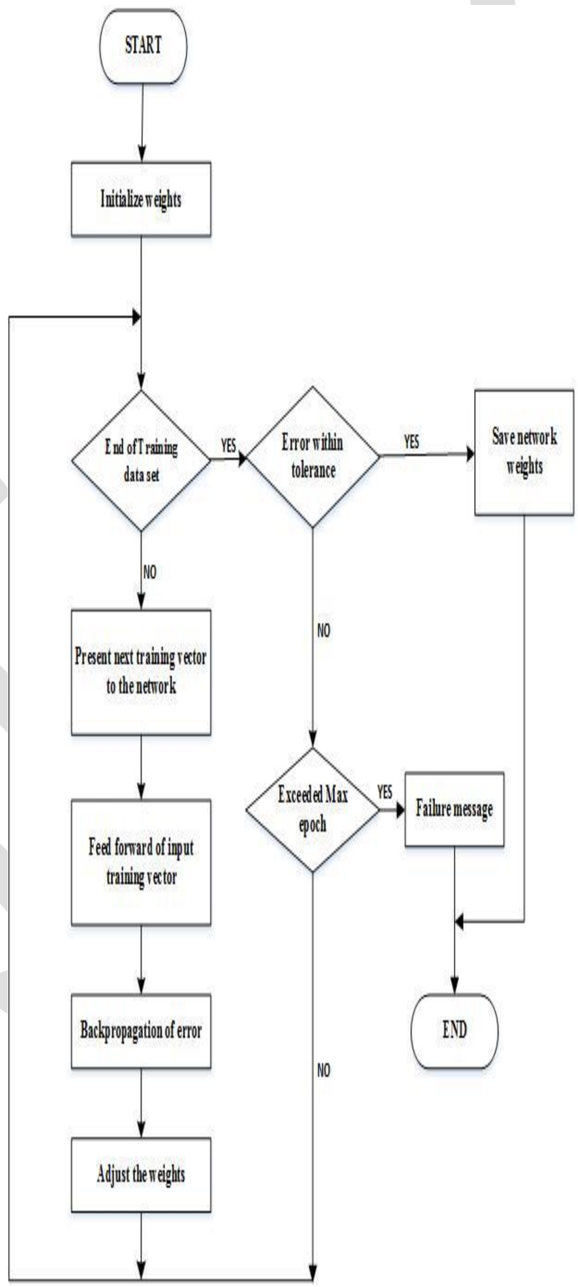

Fig-3. Back Propagation in ANN

3. PROPOSED SYSTEM

The proposed system uses the data collected from a survey of 40 Multi-Storeyed RC buildings. The raw data is in the form of layout plans. The layout plan cannot be used to train an ANN since only numeric data is intelligible for ANN. The following raw data used to compute critical parameters or features are given below.

1. Number of Columns
2. Number of Beams
3. Area
4. Height of Parapet
5. Thickness of Side Wall
6. Thickness of Interior Wall
7. Depth of Beam
8. Width of Beam
9. Breadth of Column
10. Width of Column
11. Grade of Steel
12. Grade of Concrete
13. Bearing Capacity of Soil
14. Reinforcement Area

The figure below shows a typical plan for obtaining the feature values in this work.

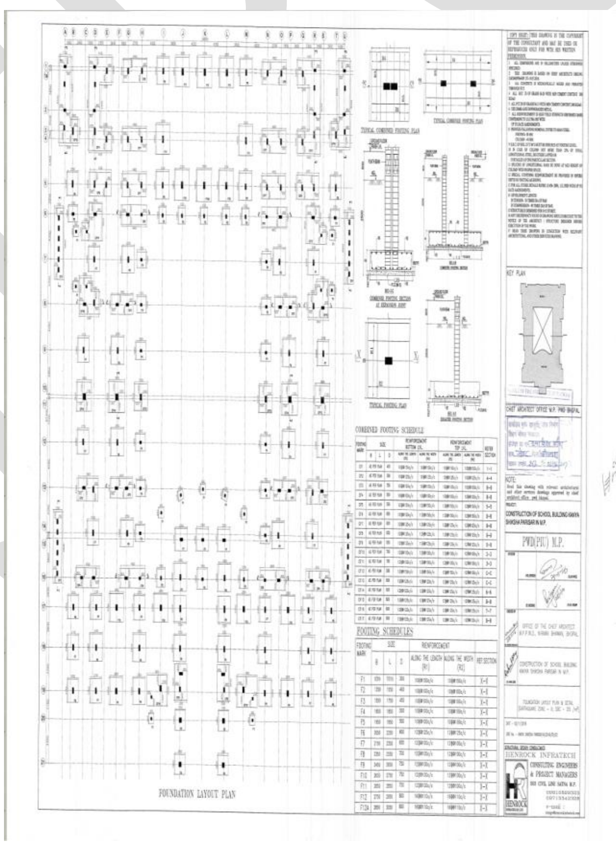

Fig-4. Foundation Layout Plan for First Building

The foundation layout plan for the first building is shown in Fig-4. Similarly the column layout plan and plinth beam framing plans yield the set of feature values used in this study. The methodology adopted in the proposed work is presented in the following flowchart.

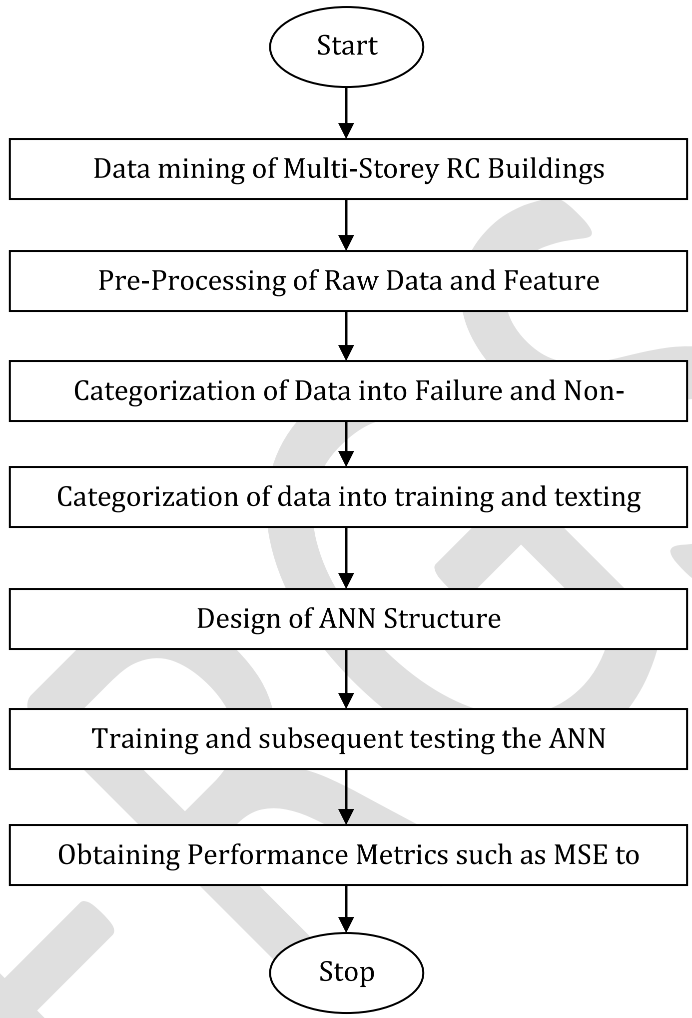

Fig-5. Proposed Flowchart

The different features can be obtained by inspection from the structure layouts. Also the reinforcement area is computed using the following mathematical Equation 6:

$$A = \frac{\pi}{4} d^2 n \qquad (2)$$

Here,
A represents the reinforcement area.
D represents the diameter of reinforcement bar.
N represents the number of reinforcement bars.

It should be noted that the performance metric for deciding the efficacy of the proposed algorithm is mean square error defined by Equation 3 and Equation 4:

$$mse = \sum_{i=1}^{n} e^2 \quad (3)$$

$$e = y_p - y_a \qquad (4)$$

Here
y_p represents predicted output;
e represents the error in prediction and
y_a represents actual output
The mean square error evades the possibility of negative and positive errors getting cancelled out thereby rendering greater accuracy to the performance of the system.

4. RESULTS

The following figure represents the neural network that has 20 neurons in the hidden layer. The proposed system is designed simulation with the help of a tool i.e. Matrix Laboratory (MATLAB 2017a). The choice of the tool has been taken as MATLAB 2017a due to the fact that it has several in built mathematical functions which render convenience in the design, training and texting of the neural network.

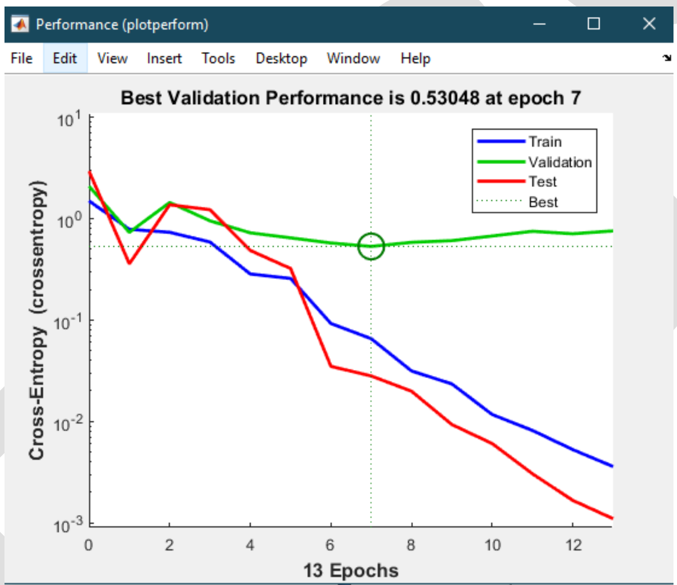

Fig-6. Training states of the proposed system

The training states show the reduction of the cross entropy which is the error metric synonymous with mean square error.

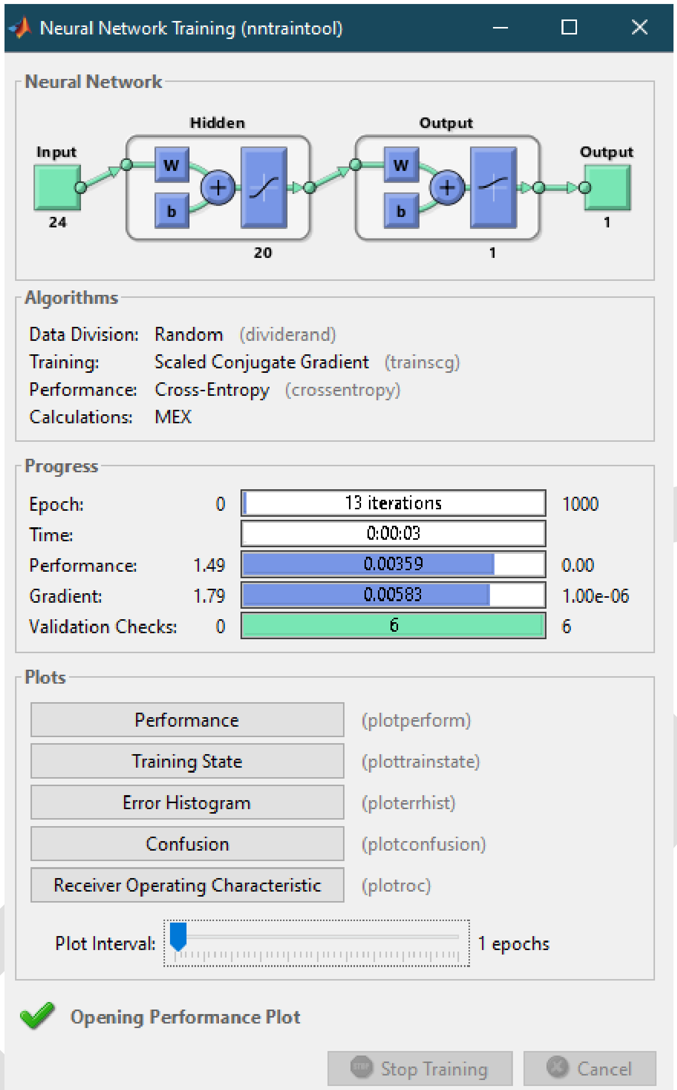

Fig-6. Neural Network with performance metrics.

It can be seen that the neural network uses the Scaled Conjugate Gradient (SCG) algorithm for training and has 20 neurons in the hidden layer. Moreover the neural network needs 13 iterations to stop training. The average error is found to be 1.49 thereby rendering an accuracy of 98.51% in feature value prediction.

5. CONCLUSION

In this paper, feature extraction has been performed from raw layout data. In overall, fourteen features have been computed from the data and have been used to train a designed ANN structure based on the Scaled Conjugate Gradient algorithm. It is found that the proposed system attains 98.51% accuracy for feature value prediction. The results can be attributed to the efficacy of the back propagation mechanism of ANNs where in the errors are fed back to the system to obtain plummeting values of errors in every successive iteration.

REFERENCES:

[1] Caglar N, Elmas M, Yaman ZD and Saribiyik M (2008) Neural networks in 3-dimensional dynamic analysis of reinforced concrete buildings. Construction Build Mater 22(5):788–800.

[2] Chen B and Liu W (2010) Mobile agent computing paradigm for building a flexible structural health monitoring sensor network. Comput Aided Civil Infrastructure Engineering 25(7):504–516.

[3] Chen J-F, Do QH and Hsieh H-N (2015) Training artificial neural networks by a hybrid PSO-CS algorithm. Algorithms 8:292–308.

[4] Chatetrjee S, Hore SS, Dey N, Amira S and Balas VA (2016) Particle Swarm Optimization trained neural network for structural failure prediction of multistoried RC buildings, Springer, January 2016

[5] Fayyadh MM and Abdul Razak H (2011) Stiffness reduction index for detection of damage location: analytical study. Int J Phys Sci 6(9):2194–2204.

[6] Han J and Kamber M (2005) Data mining: concepts and techniques, 2nd edition. Morgan and Kaufmann, San Francisco, pp 285–378.

[7] Jiang X and Adeli H (2007) Pseudospectra, MUSIC, and dynamic wavelet neural network for damage detection of high rise buildings. Int J Numer Meth Eng 71(5):606–629

[8] Mc Entire DA (2014) Disaster response and recovery: strategies and tactics for resilience. John Wiley & Sons, Hoboken.

[9] Nanda SJ, Panda G (2014) A survey on nature inspired meta-heuristic algorithms for partitional clustering. Swarm Evolution Computing 16:1–18.

[10] Pierce S, Worden K and Manson G (2006) A novel information-gap technique to assess reliability of neural network-based damage detection. J Sound Vib 293(1–2):96–111.

[11] Stratman B, Mahadevan S, Li C and Biswas G (2011) Identification of critical inspection samples among railroad wheels by similarity-based agglomerative clustering. Integrated Computing Aided Eng 18(3):203–219.

[12] https://www.ics.uci.edu/pjsadows/notes.pdf