RBF Based NN Architecture for Structural Health Analysis of Railway Steel Bridges*

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Abstract

Ambient Analysis in structural health monitoring system is a new research interest in collaboration with neural networks along with traditional methods. Mainly, steel bridges are considered for ambient analysis study including anomaly detection, predictions, localization and finally deducing some important results. Machine Learning algorithms including neural networks are efficient ways for railway bridge anomalies detection. Here a preliminary study and design of AmbinetNet is presented in addition to our base Neural Network. This base neural network consist of three hidden layers along with max-pooling and activation functions with a Softmax as a final output. Radial Basis Function is also considered in AmbientNet with additional layers. We got some promising preliminary results but as a researcher, there is always some place available for improvements. Our future based AmbientNet variations are expected to give more accurate results. As we have used ambient features for result calculations, we are also looking forward to add more features as well variation to the neural network for better results.

Keywords

Machine Learning, Neural Network, Radial Basis Function, Ambient Analysis, Structural Health monitoring.

1. Introduction

Structural Health monitoring (SHM) is becoming a field of focus to the engineers and research scientist mainly after introduction of machine learning. SHM systems are helpful in accessing the condition and integrity of structures such as bridges, buildings, pipelines, and aircrafts over time. These ML techniques (KNN, RF, SVM. ANN. CNN etc.) provide valuable insights and predictive capabilities for monitoring the structural health of such assets. SHM also provide a quantitative measure of a structure's condition over time.

Ambient analysis of railway bridges (steel or concrete) is necessary for their long life. Using Structural Health Monitoring (SHM) technology, early structural anomalies detection, occurrence of damage with alert intimation and in-time maintenance become possible. This lead researchers to do systematic structural research about dynamic responses of vibrations, natural

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frequencies, accelerations of vehicles on the bridges and temperature variations (when train passes and after train passes, in our case)[1].

Machine Learning algorithms can be trained to detect and classify different types of damage or anomalies in structures. This includes identifying cracks, corrosion, fatigue, and other structural issues from sensor data, images, or sensor fusion. These algorithms also help in how to predict when maintenance is needed based on sensor data and historical performance. This helps in scheduling maintenance activities more efficiently, reducing downtime, and preventing catastrophic failures. In bridge SHM, anomalies detection are used to detect deviations of the bridges from normal behavior which may indicate damage, wear & tear in the structures which needs attention, repair and/or maintenance.

Although Machine Learning enables remote monitoring of civil structures through the use of sensors and data communication technologies. This is especially useful for such structures in remote or hazardous locations. It is also important to note that the success of machine learning in structural health monitoring depends on the quality and quantity of data, the choice of appropriate algorithms, and domain expertise in interpreting results. Additionally, real-world applications often involve a combination of traditional engineering methods and machine learning techniques to achieve the best results in monitoring and maintaining the health of especially critical civil infrastructure.

2. Related Work

SHMs provide many viable solutions to the damage detection but most of these are only limited to anomalies, predictions or statistical model comparisons.As it can be seen that Svendsen et. al. [2] investigated statistical comparison models with supervised and unsupervised learning using Mahalanobis Squared Distance only. This study only focus of ROC metrics using KNN, RF, and SVM etc. which don't give any insights of the dataset used and the damage levels.

Similarly, Frederic et. al. [3] investigated application of machine learning methods on real railway bridges monitoring with transient relationship between air temperature and bridge temperature. He used Neural network with three input neurons in the input layer, one output neuron in the output layer giving binary results and n hidden neurons in one hidden layer.

Neves et. al. in [4] worked on different ML techniques for damage detection.In this study ANN based model is discussed for model-free bridge damage detection. Sensor based ambient features are extracted and used as an input to ANN which are collected from dynamic response of the structure in two different damage scenarios. In a review study by Onur et. al.[5] have discussed non-parametric and parametric methods for structural damage detection from the ambient data. He reviewed these methods wrt supervised machine learning algorithms. Mehrjoo et.al. [6] proposed simple ANN based bridge damage detection techniques in which he used accelerations as characteristic to calculate the damage sensitive features. Later, he developed a simple MLP with single hidden layer for damage identification and localization.

Lee et. al. [7] also used ANN model based on FE model of Hannam Grand Bridge in South Korea. They also used ambient features to perform test performance under three levels of damage. They used Probabilistic NN, Back propagation based NN and Sequential NN for results evaluations. Furthermore, Muttillo et. al. [8]also worked extensively on machine learning based

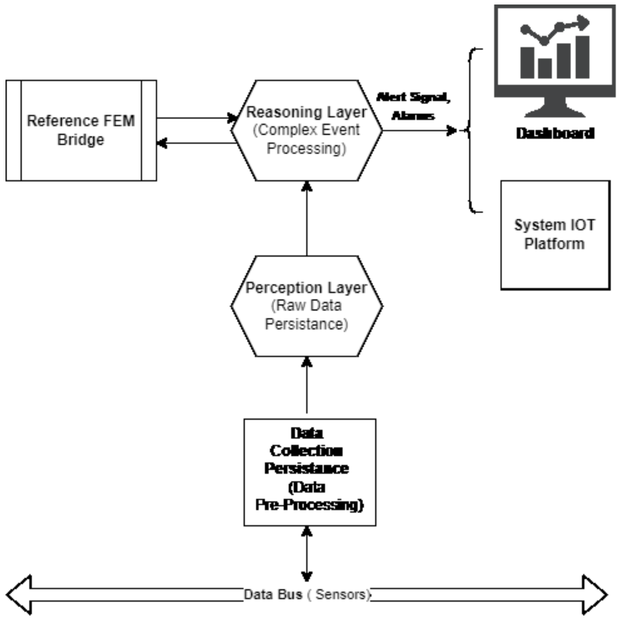

Figure 1: Overall System Architecture

model for damage detection. But this work in specifically inspired by IoT based sensory system is designed for structural damage indication. From these studies with basic ML algorithms come an idea of implementing our problem with some more deeper neural network with some variations.

3. Methodology

The aim of this research to design a system which can take input from sensors and predict anomalies in the steel bridge and also to localize the damage. So, starting form the system in Fig.1 which represents Reference FEM, the data bus for data acquisition from multiple sensors, a perception layer for raw data handling, reasoning layer for complex events processing and dashboard for generating alarm alerts.

This study focus on working with perception layer, with a functionality works around real time system having multiple accelerometers, thermisters, inclinometers etc for data collection and this data is processed for computation in the perception layer. As in this study, many sensors; accelerometer,inclinometer, thermisters etc, are being used, and only ambient study of features extracted from these sensory signals are feed forwarded to the neural network as input for anomaly detection, and damage localization in perception layer, monitoring , and alerts generation in reasoning layer. So far cumulative sum of differences, cosine similarities, crest factor, skewness, kurtosis and Stochastic subspace based identification(Single Value Decomposition) are calculated in feature extraction. These features are fed to the neural network as input.

4. Model Architecture

Initial RBF based Neural network is generated with input layer, RBF, activation functions, and other inner details of the neural net and an output layer which describes the seven scenarios for bridge sections and twenty six damage intensities. To answer why RBF is used in the hidden layer lies in a fact that they provide promising results in Structural Health Monitoring (SHM) applications for various purposes, including damage detection, feature extraction, and data analysis. However, we have used an updated version of RBFNet. This updated neural network i.e AmbientNet has four hidden layers, maxPool, leakyReLU, Batch normalization and finally Softmax for prediction.

RBF networks can be used for regression tasks to predict structural health-related parameters, such as stress, strain, or deformation, based on sensor measurements. This can be valuable for continuously monitoring structural conditions. RBF network is designed for anomaly detection and damage localization for the expected behavior of a bridge structure. Any deviation from the normal observation of the predictions indicated the damage levels and localization which can help in bridge maintenance..

4.1. RBF-Net

Radial Basis Function (RBF) network can be described in terms of its activation function and its output. The typical RBF network consists of three layers: an input layer, a hidden layer with RBF activation functions, and an output layer. The input layer receives the input data, typically denoted as x. The hidden layer contains a set of radial basis functions. Each neuron in the hidden layer applies an RBF activation function to the input data. The RBF activation function for a single neuron can be represented as:

$$\phi_i(x) = \exp\left(-\lambda_i \cdot \|x - c_i\|^2\right) \tag{1}$$

As the bridge is divided into seven sub-structures(for damage localization detection) and in simulated architecture; different damage intensities are applied, it is important to note that RBF networks require appropriate training data that includes both healthy and damaged structural states. Additionally, the choice of network architecture, including the number and placement of RBF neurons, can have a significant impact on their performance. Furthermore, our ambientNet composed of a fully convolutional layer followed by an RBF function, batch normalization, leakyReLU as activation function, max-pooling and in the a softmax activation. For our input data this model with some variations is used for the preliminary results.

5. Preliminary Results

For our designed neural network, we used ambient features as input to it and as a result we got some promising preliminary results. As we have two different output scenarios i.e. 26 damage intensities(simulated data) and 7 bridge section(real bridge is divided into seven subsections), Fig.2 shows the ROC curve of both the output scenarios.

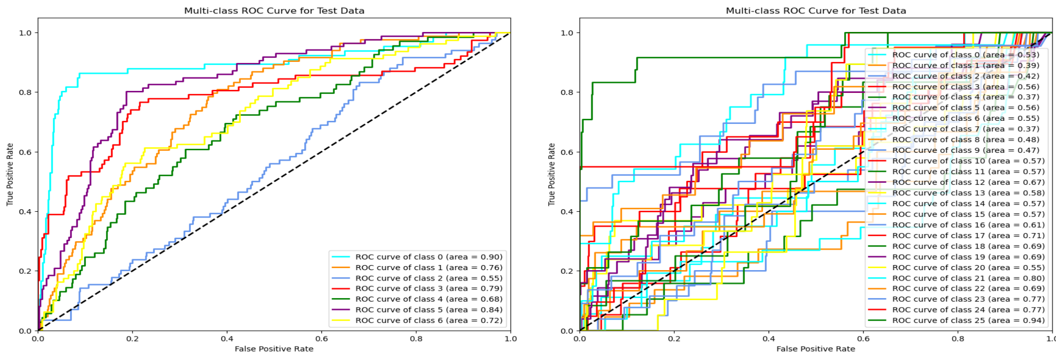

Figure 2: ROC Curve of Bridge Sections(Left) Bridge Damage Intensities(Right)

The results shows that for damage intensities scenario, Fig. 2 (Left) there are some low prediction results for central classes whereas in Fig. 2 (Right), we observe class 5 and 6 shows low positive results.

6. Conclusion

This paper presents the application of a Neural Network based SHM system architecture with a basic RBF-Net for detecting damage, localization and alert system for railway steel bridge. Although NN algorithms are generally used for image classification and object detection.Structural Health Monitoring (SHM) systems are in implementation of a damage detection and classification strategy for engineering structures. However, we have tried to use neural network for anomaly detection using vibration responses captured from different sensors installed on the real time railway bridges.

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