COMPARISON OF STATE-OF-THE-ART MACHINE LEARNING BASED DATA DRIVEN AND MODEL UPDATING METHODS AGAINST SHALLOW AND DEEP CONVOLUTIONAL NEURAL NETWORKS METHODS OF STRUCTURAL DAMAGE DETECTION

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Abstract. *Traditional methods of damage detection on civil structures included approaches depended on human judgement and hence required highly skilled persons. Thus to overcome this problem of damage detection, Machine Learning (ML) algorithms were introduced which were more diligent than the traditional methods and Deep Learning algorithms are usually a subset of the machine learning algorithm. Over the years many research case studies have been conducted on ML algorithms and Deep Learning (DL) algorithms and their applications in structural damage detection, but very few have tried to compare the two algorithms and provide the reasons of how DL algorithms are more efficient in damage detection process. Thus this study shall examine the applications of ML based data driven methods of damage detection and compare it with ML based model updating methods to provide a clear understanding of how data driven methods are more economically feasible as compared with physics guided model updating methods. Also shallow and deep CNN (Convolutional Neural Network) based approaches which are termed as DL algorithms shall be investigated and shall be compared with the ML based methods, to provide the reasons of transition. Lastly this study shall show how to obtain simulated data (for both damage and undamaged/intact scenarios) for training as real time data is not readily available for civil structures and since both ML algorithms and DL algorithms are data hungry processes, hence more the training of the algorithms, more shall be the accuracy of the damage detection process.*

Keywords: Damage detection, Parameter estimation, Data driven methods, Physics guided methods, Model updating, Dynamic response, Deep Learning, Convolutional Neural Networks,.

1. Introduction

Damage detection is the important principle for Structural health monitoring (SHM) based methods and early and diligent structural damage detection is the main objective for SHM based method applications [1]. Damage can be accumulated on structures through (deterioration, corrosion, creep and shrinkage and due to fatigue etc, which are caused due to environmental factors or human inducing factors. Detecting structural damage is very important for strengthening and maintaining the service life of civil structures. Traditional methods of structural damage detection (SDD) were conducted through visual inspection which is a primary non-destructive testing (NDT tests). And with time many NDT tests were evolved like the Ultrasonic testing(UT), radiographic testing(RT), magnetic flux leakage(MFL) and digital image correlation(DIC) and various other tools. Below in Fig 1.1, NDT based (UT) is conducted on a girder beam of a bridge.

Figure 1.1 UT based visual inspection

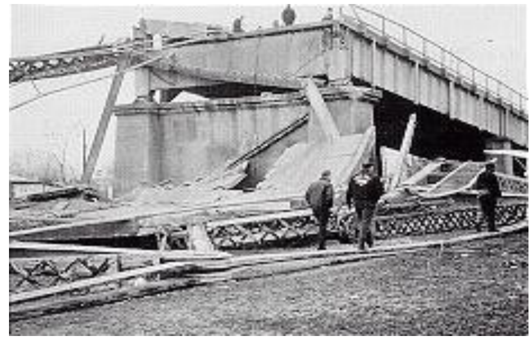


Figure 1.2 Silver bridge collapse, Ohio

(Figures adapted from NDT resource center)

From the NDT resource center [2], it was inferred that visual inspection through (NDT) tools were not sufficient for SHM of large-scale civil structures. The major drawback of such NDT based methods could be explained through the case study on I-35W Mississippi River bridge collapse [3]. I-35W Mississippi River bridge was an eight lane, steel truss arch bridge and had a tragic failure on August 1, 2007 killing 13 people and injuring 145. Several NDT inspection tests had been coordinated since 1990 like the strain gauge testing, and the I-35W bridge was declared as "structurally deficient". According to the study conducted by the civil engineering department of University of Minnesota, cracking had been previously discovered in the cross girders, through NDT tests and the report suggested that I-35W was needed to be retrofitted or replaced. But the project was cancelled as the bridge engineers favored periodic safety inspections through NDT tests. Thus the collapse of the I-35W could have been prevented if the bridge engineers had used the advanced structural damage detection tools, For example FE(Finite element) Model analysis could have predicted the increase of further stress which shall induce the crack propagation and hence would have been more superior than periodic inspection and thus it can be inferred that NDT tools are not sufficient for SHM for large scale structure as they could not predict the damage location and damage intensity. Also it can also be concluded that NDT tests requires high skilled persons and good knowledge of detecting damage, and that the process of regular inspections is time-consuming and laborious.

Thus overtime, more advanced detection tools were required and hence evolved, machine learning algorithms in structural damage detection. Machine learning (ML) is an advanced intelligent algorithm model which is capable of acquiring knowledge from a series of available data, and the main principle of a machine learning algorithm is to learn by example and training and pattern recognition, in a human –like manner. There have been many examples of using machine learning based data driven methods in structural damage detection, Lee et al.[4] showed by using artificial neural networks, the shear strength of FRP- reinforced concrete flexural members(without any stirrups) could be predicted.

Although there have been numerous research works conducted using different machine learning tools for parametric and non-parametric structural damage detection , but only one research work , Avci et al.[1] showed the need for moving from traditional methods to machine learning methods and deep learning methods for damage detection and showing the efficiency and superiority of using Deep learning (DL) algorithms. But this study did not elaborate the importance of training data on deep learning algorithms and also did not included the study of obtaining the data for the damage scenarios as in civil structures the training data sets for the pre and post damage (undamaged and damaged) cases are very rare and not available. Also the methods of physics guided model updating and its integration with ML algorithms and its SDD application have not been discussed. Thus the argument lies : "Why and How Deep learning algorithms are more structured and well efficient than Machine learning algorithms?" , and "How and Why we need to obtain large number of training data sets for the correct prediction of damage?" and also " How shall we obtain a data-set for damage scenarios in the absence of measured damage data?"

The rest of the study has been organized as following: providing a general background on Structural health monitoring and structural damage detection. Introducing ML algorithms and the different Data Mining or data driven methods build on ML algorithms. Reviewing the study of the Data driven based ML algorithms by reviewing a list of previous case studies. Reviewing the study of ML based model updating methods of SDD applications. The study of Shallow and Deep CNNs and its efficiency in SDD applications. Lastly concluding this study by comparing the 3 methods and recommending future research study works.

1.1 Methodology:

For this study, the author has reviewed a total of 49 research case studies related to introducing the SHM and ML and DL fundamentals and machine learning based data driven and model updating methods and deep learning (focusing on CNNs) based structural damage detection and shall compare the three methods and comment on the optimum choice for Structural damage detection method through a critical examination of the studies. Also studies on creating simulated training data for the algorithms have been reviewed.

- The research case studies/articles were collected from widely known databases including Scopus, Research gate, Science direct, ASCE library, Sematicsscholar.org.

2: Structural Health Monitoring (SHM)

2.1 Objective of Structural Health Monitoring

Health monitoring of a structure is the process of damage identification and assessment of engineering structures through the use of sensor systems and related hardware and software facilities Aktan [5]. It involves a process of periodically analysing the structural response and operational environmental measurements through a series of sensors and thus evaluating the present and future state of response of the structure. The main objective of SHM is to identify the structural damage and assess the health of the structure using monitored data. Also, Brownjohn [6] emphasized the need for rapid assessment of civil structures when acted upon by severe earthquake and typhoon events. Damage prediction forecasts the performance of a structure by estimating the current damage pattern and evaluating the future loading patterns for the structural system and hence predicting the remaining life of the structure through computer simulations or analysing the past damage patterns.

2.2 Damage Identification

Damage prediction is the main objective of SHM. Damage prediction is the estimation of an engineered structure's remaining service life which is based on the output of simulation models that develops the behaviour performance by combing the past, present and predicted future environmental and operational conditions. In Structural health monitoring apart from damage it is also important to identify certain change in material properties, For: Change in stiffness of a reinforced concrete member thus affecting its strength and serviceability requirements or how a minimal surface rusting of reinforcements might increase the interface bond and yield high performance for reinforced concrete members [7] Farrar et al.[8] interpreted the importance of Damage prediction in SHM outlining the objectives of structural health monitoring system as :

Objective 1: Detecting structural damage, thus indicating the presence of damage in the structure

Objective 2: Location of damage, thus indicating the probable position of damage

Objective 3: Classification of damage, relevant information of the type of damage

Objective 4: Damage assessment, predicting the degree of damage

Objective 5: Future damage prediction, thus evaluating the current damage and estimating the future serviceable life of the structure. Thus these objective provides the knowledge/information of the state of damage.

2.3 Evolution of SHM methods

Structural health monitoring methods based on change in dynamic characteristics have been studied for the last three decades which can be traced back to the time when tap testing (on train wheels) where used for fault detection. Interest in the field of research in SHM generated since the 1980s with the structural damage assessment of offshore platforms. SHM methods can be broadly categorized as "Local health monitoring methods" and "Global health monitoring methods" [9]. Initially, Non-destructive testing (NDT) methods which were "local health monitoring methods" were used for damage assessment of engineering structures. Like ultrasonic waves to analyse the extent of stress generation on structures or eddy current methods for locating cracks. They were time consuming and expensive and even not efficient for damage prediction of complex structures. Whereas global health monitoring methods were used, which could determine the overall performance of a monitoring structure thus indicating the present and future condition of the structure. Global based methods are of two types Vibration and non-vibration. In Vibration based methods were further classified into parametric (computer model based methods) and non-parametric (signal based methods).[9] Hence the field of structural health monitoring have seen a load of advances in various branches of technology which included sensing instrumentation, data processing, data signal acquisition and transmission and lastly numerical simulation and computer modelling.

2.4 Barriers and Future of SHM

Structural health monitoring methods (SHM) have still got significant barriers to the damage identification system. Some of the Technical Barriers could be elaborated as follows [9,10]:

- Technical challenges to vibration based methods are that damage is mostly a local phenomenon and damage does not importantly influence the lower frequency of a global structural response which are usually the measured response.
- A challenging problem for SHM methods are that in absence of damaged data, the feature selection and damage detection cannot be performed efficiently. Also the selected feature shall be sensitive to small damage patterns: like a fatigue crack at a component of a structural frame.
- Also that the loading which creates the response we are measuring, and later analysing on a structure is mostly unknown.
- Variation of temperature and other environmental factors affect the civil structures by affecting the stiffness, thus accounting for these in the damage identification process is also challenging

Thus it can be assumed that SHM methods in real civil engineering applications could be a challenging factor for damage detection because of the complex patterns.

3: Machine Learning Algorithms and its applications

3.1 Introduction to Machine Learning Algorithms

Artificial Intelligence (AI) is the field of computer science which was aimed in developing the machines to solve the problems which were challenging for humans but were effortless for computers. AI systems were earlier knowledge based systems to solve problems by using "IF" and "Else" statements which were designed by human experts [11] . But knowledge based system have failed to conduct "Day to day" tasks which were uncomplicated for human beings for example: image recognition, object detections and speech recognitions, because large amount of training needed to be done to conduct such intuitive tasks and hence this was a drawback for knowledge based artificial intelligence systems. Thus machine learning algorithms (ML) were introduced to overcome the drawbacks of such knowledge based systems. Through machine learning algorithms, computers can "Acquire" the knowledge for carrying out specific tasks by analysing a set of large amount of data[1]. But before analysing the data, pre-processing of the data is required to extract a certain amount of features which shall be required to prepare an input data set , this process is usually defined as " Feature Extraction"[12].

3.2 Hierarchy of Artificial Intelligence, Machine learning and Deep learning (DL) algorithms

The relationship among AI, ML and DL[13] could be explained by the figure below

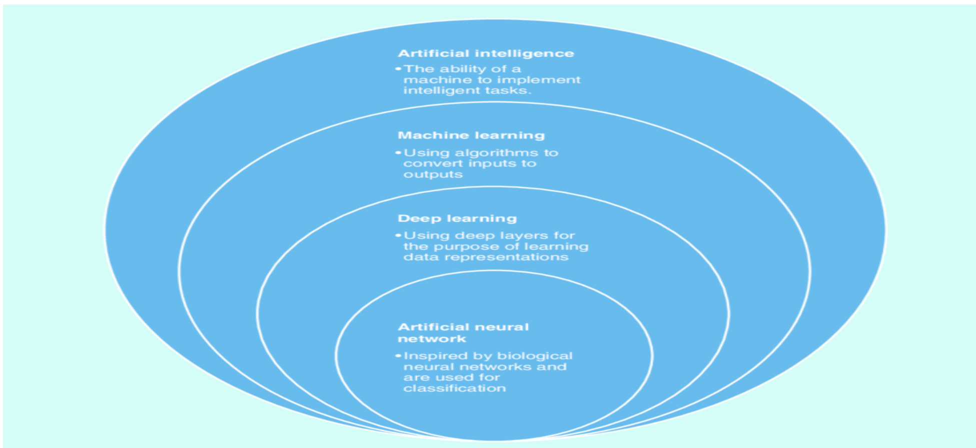


Figure 0.1 Hierarchy of AI, ML and DL algorithms (adapted from [13])

Thus comparing the AI, ML and DL, the relationship of the three could be explained as AI is the subset of Data science and Machine learning is the subset of AI and Data science and Deep learning is the subset of machine learning, AI and data science. Thus, AI usually represents the simulated intelligence in machines whereas Machine learning is the practice of training the machine to acquire knowledge to make decisions and Deep learning is the process of solving complex problems for which machine learning algorithms are not efficient, and lastly artificial neural networks are the biologically feed forwarded algorithms for automatic discovery of data patterns for detecting the features. Studies in the field of medical sciences could explain machine learning algorithms in an uncomplicated manner, for example machine learning algorithms are used to predict the type of cancer a patient suffers, by using a large sample of data sets consisting of medical diagnostic observations of previous patients which were used as the input set and the output (type of cancer and whether it is benign or malignant) is obtained.

3.3 Learning methods of machine learning algorithms

Methods of Machine learning algorithms are classified in 3 types [14]:

- Supervised learning methods, wherein the input data set has a "label" known that can be assigned to each data set and the model shall be prepared through the training data set process and predictions can be altered.

For example: in damage detection, supervised learning are the cases for which the data from the undamaged and damaged conditions are available. Commonly used algorithms for supervised learning methods are back propagation neural network and logistic regression

- Unsupervised learning methods, wherein the input data set does not have a "label" known and hence prediction of the results can be done by extracting the information from the input data or by gathering the useful information from the reference structure.

For example: in damage detection, unsupervised learning are the cases where the data is only available for the undamaged condition and the damaged extent or output shall be interpreted by extracting the information from the undamaged case. Commonly used algorithms for unsupervised learning methods are AR (auto-regressive) model, ARMA (auto-regressive moving average) model, MA (moving average) model and gradient descent methods

- Semi-supervised learning methods, wherein the input data set are a combination of labelled and unlabelled. Thus, the model shall have to organize the data set and learn from the underlying structures and predict the output results. Commonly used algorithms are extensions of the supervised and unsupervised learning methods by making suitable assumptions of modelling of labelled data.

3.4 Data Mining or data driven methods built on ML algorithms

Data Mining (DM) is a process of Knowledge discovery from a set of database, Gordon et al.[14] explored the process of building data mining methods on ML and DL algorithms and showed its applications on damage detection of structures. Certain works of Data Mining methods include clustering (by dividing the data samples into similar groups) , prediction (by determining the patterns for predicting a set of target results), classification (by classifying and matching an unknown data to a set data base) and exploration and association (by exploring an input data set and associating it with the output set).

The performance of a data mining based machine learning algorithm usually depends on the size , high dimensionality of the data represented and the cleanliness of the dataset.[15]

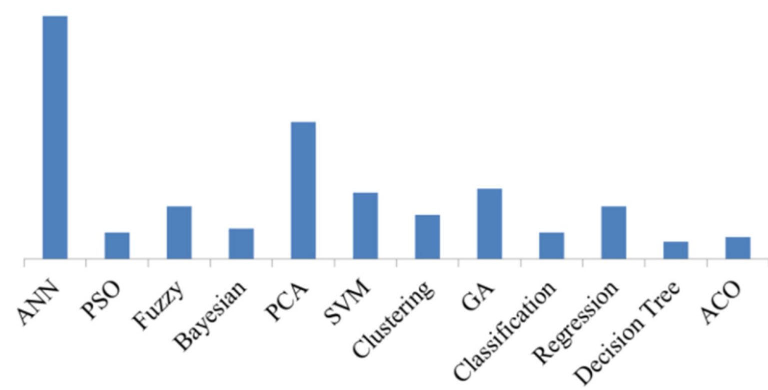


Fig 3.2: DM applications in structural damage detection adapted from[14]

As shown in figures 3.2 and 3.3, since 2000 there were 3 main data mining techniques used in structural damage detection , ANN (Artificial neural network), PCA(Principal component analysis) and GA(Genetic algorithm). And the percentage record of DMT in SDD shows that ANN and PCA have received the highest application rates where 30% and 20% of the researches were conducted with these two methods. Hence this study shall consider only the ANN method of data mining and learn its applications in SDD and used the studies for comparison.

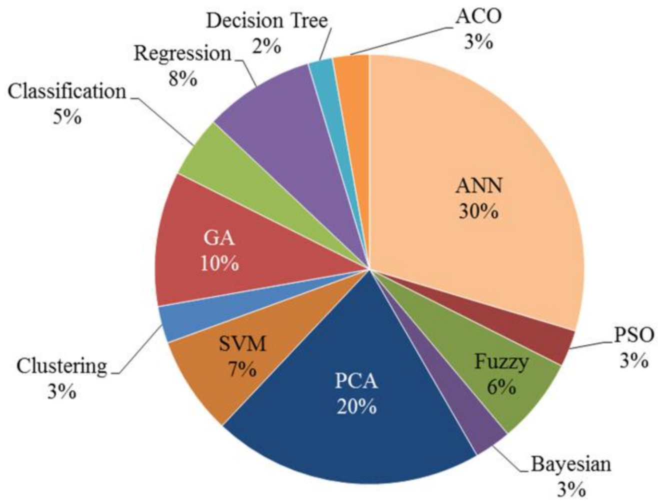


Fig 3.3: Percentage of DM applications in structural damage detection adapted from[14]

4: Machine learning based data driven parametric and non-parametric methods of SDD

As discussed, vibrations based methods are divided into 2 classes parametric and non-parametric, where parametric damage detection methods are basically model based approaches where computer simulation model are created to extract the dynamic properties. Whereas in non-parametric approach, the structural damage detection is directly interpreted from the acceleration signals and are thus referred as signal based approach. Data-driven approaches based on ML algorithms as explained are commonly referred to as “Data hungry” [1]. Hence data driven methods are required to be trained with large sets of data, and with large sets of training data, it can predict the output results with more accuracy.

4.1 Parametric structural damage detection (SDD) methods using machine learning algorithms

Thus in most global health (parametric methods based on ML algorithms), the damage identification were evaluated by determining the modal parameters of the structural system like the natural frequency and mode shapes which were extracted and introduced as the input data, and for classification process certain classifiers like artificial neural networks were used. As the process shall be shown in the studies below.

4.2 Supervised Learning Data driven based SDD applications using ANN model algorithms

In the first study, damage detection on a fixed-fixed beam using Fourier coefficients as input data and neural networks for prediction was proposed by Prashant et al.[16]. The author’s developed a parametric model of the beam by dividing the fixed-fixed beam element into 20 small elements, as shown in Fig 4.1

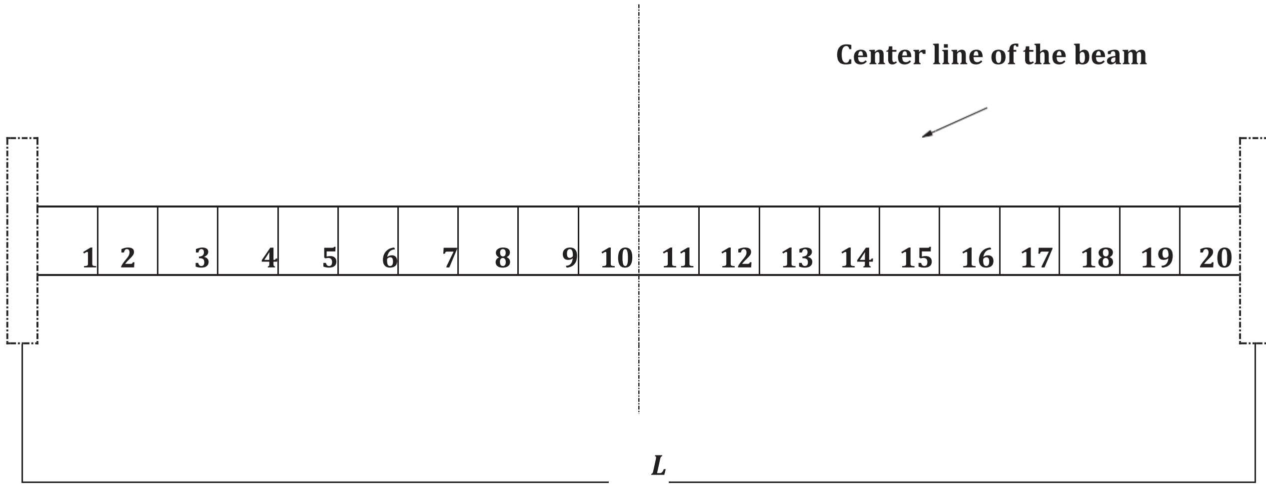


Figure 0.1 Model of the beam used (fixed –fixed end condition)

And hence after providing a free vibration, the acceleration response was recorded and Spatial Fourier analysis was used to interpret the mode shapes. In this study, the author's used Fourier coefficients as the input data set for the neural network. The input data were obtained from 10 different parts of the beam for 5 damage levels. And the corresponding outputs were the centre of the damage part and damage levels. Hence the Fourier coefficients for particular modes were obtained using analytical and FE model Structural damage was modelled by reducing the stiffness of the cross section of the beam. Thus FE Model were developed to inspect the damage extent in the beam by comparing the Fourier coefficients value of the mode shapes. Since the beam element were divided into 20 small elements, the damage extent was varied between 0-50percent. Thus it was concluded that Fourier coefficients which were zero for the undamaged beam were having non-zero values and thus indicating damage in the fixed-fixed beam elements. Feed-forward and back propagation algorithms were used as ML algorithms and the number of neurons in the hidden layers and the structure of the hidden layers were optimized by changing the parameters like weights and biases to minimize the error and achieve an optimum condition. The sigmoid function (linear activation function) was used to forward the input data to the output data set. Thus 3 modes were selected with their corresponding Fourier coefficients for the study and 3* 11 = 33; 3* 15 = 45; 3* 21 = 63. Hence the neurons were estimated as 50 for 33 input data set; 75 for 45 input data set and 100 for 63 input data set. The argument that could be interpolated is that even though ANN through spatial Fourier analysis could be used for SDD, but this method was needed to be experimentally proven on a real structure and also in case of absence of damaged data, this method of analysis could not be proved efficient.

In the Second Study, damage detection of the truss bridge joints using Artificial neural networks was proposed by Mehrjoo et al.[17]. The author's proposed that the identification of the parameters of the structure from the measured vibration response could be understood as an Inverse Problem, where the behaviour of the internal structure of a physical system could be interpolated by identifying the unknown input, giving rise to the measured output signal. In this study the damage intensities of the joints for truss bridge structure were estimated using a back-propagation algorithms. Natural frequency and mode shapes were used as the input parameters to the neural network. The network was trained with a data set of assumed damage percentage of joints as outputs. Thus the value in each neuron indicating the percentage of damage of a related joint. The author used an example of the Louisville Bridge in the United States which is a two-span planar truss structure and the dead loads were assumed and defined in the joint locations. The natural frequency and mode shapes of the truss structure were used as the input data set and the objective was to estimate the percentage of damage of 16 unknown joint locations based on measured modal response data. But rather than identifying the Percentage of damage of the whole structure, the author used a Sub-structuring technique where the structure was divided into 3 sub-structures as shown in Fig 4.2 and thus the percentage of damage of the internal structure was estimated.

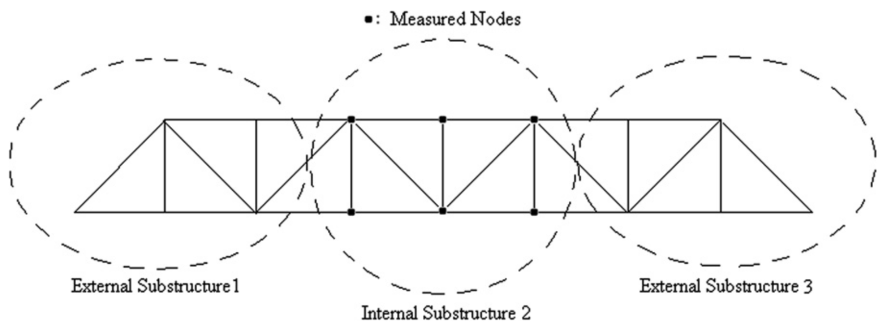


Figure 0.2 Model of the beam used (fixed –fixed end condition)

And for the training process, the first five bending modes were considered as shown in Fig 4.3. Damage scenarios were introduced by reducing the stiffness of the truss members. 75 epochs (1 epochs means an entire dataset is passed forward and backward through the neural network only ONCE [18]) were considered and hence the network was trained for this optimal epoch. Thus the method proposed by the author were capable of detecting the location and severity of damage in the truss structure with great accuracy, and though the introduction of the method of Internal problem and dividing the structure into sub-structures were optimum choices and provided with optimum results , but 2 arguments can be introduced: Firstly, the damage scenarios were introduced manually and the neural networks was trained through them, but the damage scenarios would not be similar for a different or same structure pattern and it would be required to change the damage scenario and hence leading to more computational time. Secondly, also with the change in parameter of the structural system, feature extraction process have to be conducted simultaneously every time and hence would again lead to more computational time. Thus, DL algorithms could be an optimum choice which can use the same principles adopted by the author's but convolute the feature extraction process and classification process into one step and save the computational time efforts.

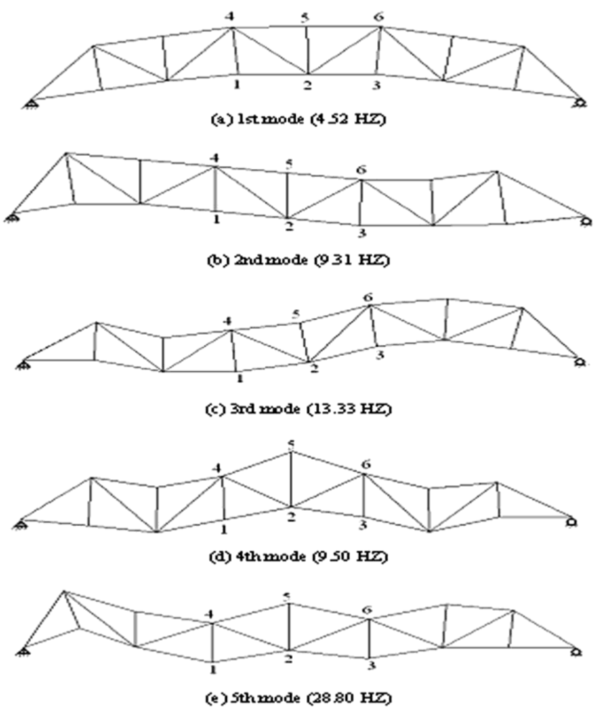


Figure 0.3 First 5 bending modes, as considered by Mehrjoo et al.[17]

International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 07 Issue: 12 | Dec 2020 www.irjet.net p-ISSN: 2395-0072

In the Third Study, Bayesian Probabilistic approach for structural health monitoring was proposed by Yuena et al.[19], where the author introduced the concept of damage detection on a pattern matching approach using dynamic response data. Patten matching approach was proposed were the structural damage were estimated through a change of modal parameters and hence an indicator of damage for all damage cases of a structure was interpolated through it. Thus the damage indicator(DI) of all possible damage cases were examined and matched with the measured DI (through modal identification process) and the damage case relating to the best fitting DI were treated as the possible damage case. The author used an example of a model of a five-story building as shown in Fig 4.4, and 5 damage locations and extent of damage were assumed (0%, 20%, 40%, 60% ,80%) and the damage extent were shown as reduction in stiffness of the member. But since there would be 3125 total no of damage patterns for 5 damage cases and it would be lead to high computational time, they decided to divide the process into 2 phase manner, where in the first phase, the damage locations were identified by using an ANN with damage signatures as the input data set. And in the second phase, the extent of damage in the first phase were identified by using another ANN with the change in modal parameter as the input data set. For optimizing the ANN model, Bayes probability theorem was used and various combination for the optimum hidden neurons were investigated and the author's came to a conclusion that 6 number of hidden neurons would be the optimum selection for the ANN model. Thus the proposed model was capable of predicting the damage location and extent of damage and hence Bayesian Probability approach was also capable of providing the optimum choice of no of hidden layers and no of neurons in the hidden layers.

Though the proposed method was able to detect the damage and optimize the function of the ANN model, the methods was not tested experimentally and also the proposed methods shall require computational time because for every damage location, the extracted features shall be needed to be hand-picked.

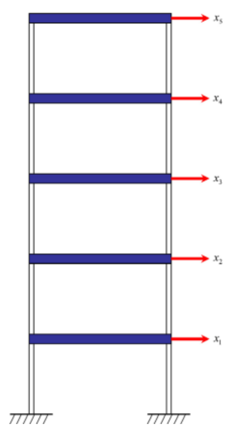


Figure 0.4 5 Storey building frame model (adapted from [19])

In the Fourth study, Ng [20] proposed an extended Bayesian Probability ANN approach, which was an extended study of Ng et al.[21], to examine the damage on a simulated benchmark structure. Pattern recognition was proposed by the author, to match the pattern of the measured and calculated damage patterns and the change in modal parameters were utilized as a vector of the pattern feature for damage detection purpose and the ANN was trained to determine the extent of damage and location of damage. The benchmark structure was a four-storey 2x2 bay model frame which was conceptualized in 3D Finite element model using MATLAB software. Six damage cases with different amount of damage extent was studied and the change in horizontal stiffness in x and y direction was examined.

Actual percentage reduction in horizontal stiffness of each storey for each damage case.

Case	Direction	Storey			
		1st	2nd	3rd	4th
DP1B	*x*	**11.31**	0.00	0.00	0.00
	y	0.00	0.00	0.00	0.00
DP2B	*x*	5.66	0.00	0.00	0.00
	y	0.00	0.00	0.00	0.00
DP3B	*x*	11.31	0.00	5.66	0.00
	y	0.00	0.00	0.00	0.00
DP3Ba1	*x*	5.66	0.00	2.83	0.00
	y	0.00	0.00	0.00	0.00
DP3Ba2	*x*	3.96	0.00	1.70	0.00
	y	0.00	0.00	0.00	0.00
DP3Ba3	*x*	2.26	0.00	1.13	0.00
	y	0.00	0.00	0.00	0.00

Identified percentage reduction in horizontal stiffness.

Case	Direction	Storey			
		1st	2nd	3rd	4th
DP1B	*x*	**10.96**	0.20	0.00	0.00
	y	0.00	0.00	0.07	0.00
DP2B	*x*	5.79	0.54	0.00	0.00
	y	0.00	0.00	0.00	0.03
DP3B	*x*	11.38	1.20	6.22	0.00
	y	0.00	0.00	0.01	0.06
DP3Ba1	*x*	6.23	0.60	2.90	0.00
	y	0.04	0.00	0.12	0.00
DP3Ba2	*x*	4.12	0.48	1.82	0.00
	y	0.02	0.00	0.09	0.00
DP3Ba3	*x*	2.54	0.65	1.23	0.00
	y	0.03	0.00	0.10	0.00

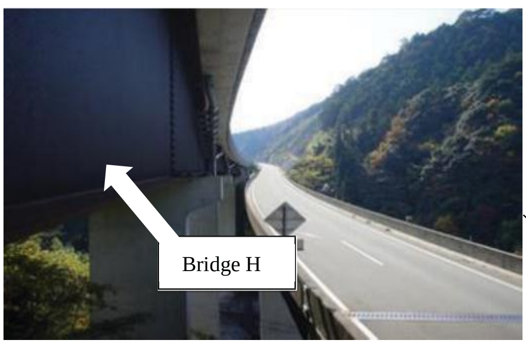
Table 0.1 Comparison of the actual and measured percentage reduction in horizontal stiffness[adapted from 20]

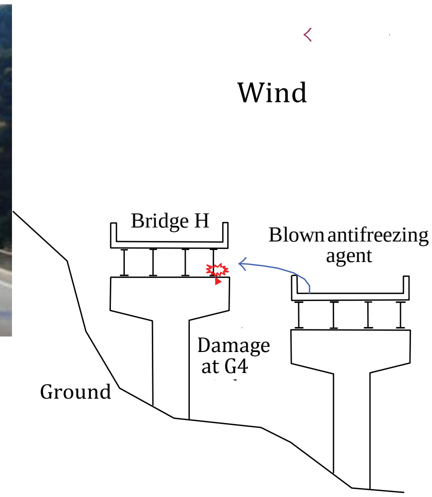
4 damage locations were chosen in x and y directions and the extent of damage was estimated as change in inter-story stiffness. 113 damage patterns were inspected in each x and y directions. ANN model were prepared for x and y directions, ANNx and ANNy and extended Bayesian approach was used to optimize the no of hidden layers and the corresponding no of neurons in the hidden layers. Thus the trained ANNx and ANNy were utilized to examine the reduction in stiffness in x and y directions. From Table 4.1 (adapted from [20]), it was shown that for the first storey the actual percentage reduction (11.31%) is very close to the measured percentage reduction (through damage detection using ANN models) (10.96%) and hence the proposed method were successful in detection of damage on the benchmark structure. But the argument lies again that the damage locations and patterns had to be hand-selected.

4.3 Non-Parametric based structural damage detection (SDD) methods using machine learning algorithms

Mostly machine learning algorithms are also used for creating non-parametric based structural damage detection methods. In non-parametric based approach, the feature extraction process is carried out by extracting the vibration responses from a reference structure using signal processing techniques, unlike in parametric model where FE simulation models were used for feature extraction. The extracted output of the signal processing techniques are processed through ML algorithms for structural damage identification and localization. Various feature extraction and classifier combination are investigated in Non-parametric SDD approach literature.

The first study involves a non-parametric approach of SDD proposed by Chun et al[22] , for observing the corrosion inducing thickness reduction of the girders in bridges as shown in (Fig 4.5, (a)) . The damage due to corrosion has occurred due to blowing of the anti-freezing agent from the bridge below thus causing severe damage to the external girder as shown in (Fig 4.5 (b)). The acceleration response was extracted from 18 positions of the girder and the features extracted were the characteristics of the acceleration signals which were the maximum and variance of the signals calculated from the time-series data analysis.





(a) (b)

Figure 0.5 (a) Panoramic view of the exterior girder of Bridge H and (b) How Girder of Bridge H is corroded adapted from Chun et al[22]

The extracted features were then processed through a Multi-Layer Perceptron(MLP) algorithm for evaluating the integrity of the structure, and for the training of the ANNs FE(Finite element) simulation models were used to analyse the bridge, The ANN model had a single hidden layer with 20 neurons and the accuracy of the model was investigated by a method of Leave-one-out cross validation as shown in (Fig 4.6) and it was found to be successful. Thus the proposed method was found to be successful but since the method was numerically verified but not tested on a real bridge model and hence a general statement could not be made on the work.

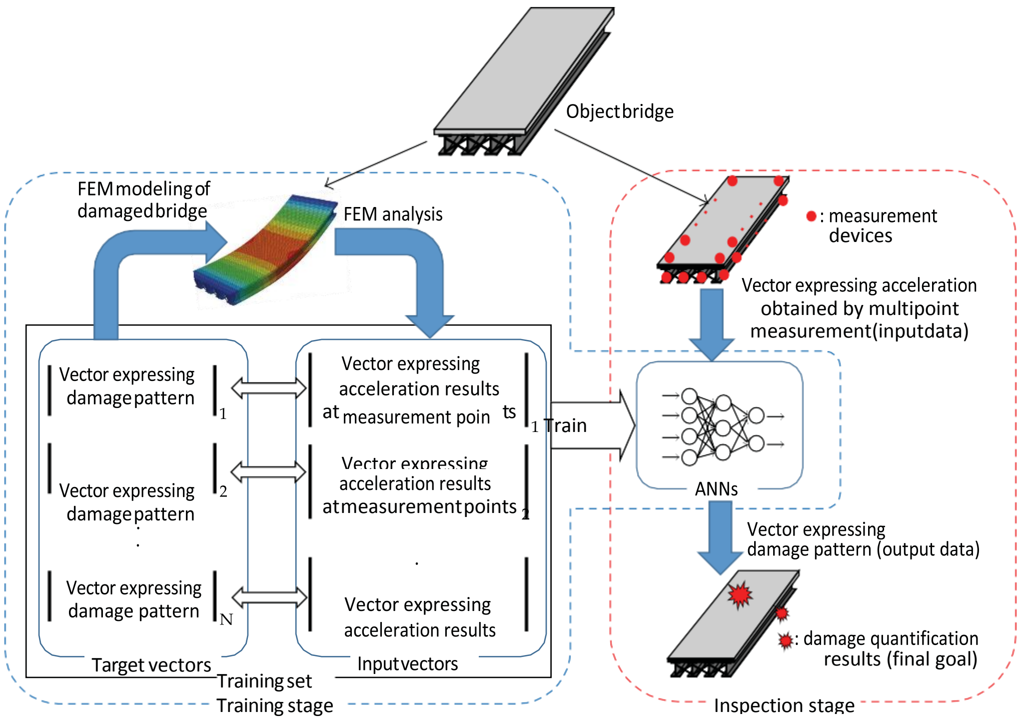


Figure 0.6 Methodology of the proposed work of damage quantification as used by Chun et al[22]

Over time researchers concluded that maximum and variance values of acceleration signals were not an effective option for feature extraction as they were sensitive to operational and environmental conditions and hence more investigations were conducted for optimum feature extraction process from signal processing techniques and hence most of the current approaches used were Wavelet transformation and Auto-regressive model from the time series data analysis and were used as extracted features.

In the second study , Yam et al.[23] proposed a damage detection method on a PVC sandwich panel using wavelet transformation and combining with neural network for damage identification. The authors proposed to detect crack damage on a PVC sandwich plate as shown (in Fig 4.7) where vibration responses were extracted through Wavelet Packet Analysis (WPA) from 120 damage cases of the PVC sandwich plate of dimensions Length(L),Width(B),Depth(H) as 295mm*98mm*8mm by exciting the plate with a square waveform . 4 locations were chosen and 30 different crack lengths from 0% to 15% of plate width were introduced at each crack location. A BP algorithm was modelled with 32 input neuron and 4-output neuron and 16 neurons in the hidden layer as shown (in Fig 4.8). 108 were used for training the ANN algorithm and 12 sets were used for validating the performance of the model. The study was concluded with successful identification and location of damage through ANN, thus proving the efficiency of damage detection through non-parametric methods.

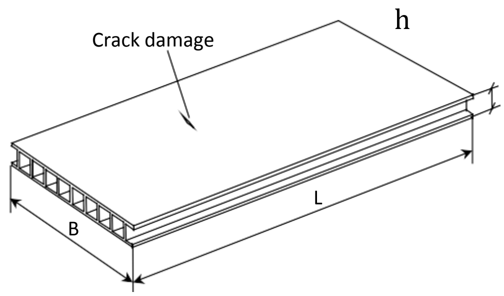


Figure 0.7 Numerical model of PVC sandwich panel with crack as used by Yam et al.[23]

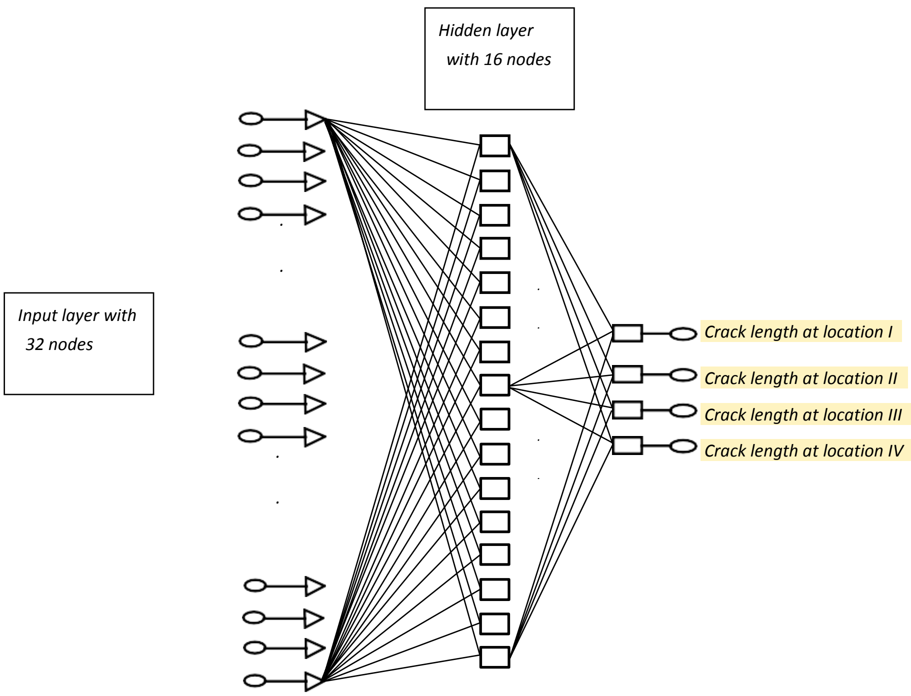


Figure 0.8 ANN classification for crack identification as adopted by Yam et al[23]

4.4 Conclusion and Discussion

Thus after the critical review of the studies on ML based data driven methods for SDD, it can be concluded and argued that even though ML algorithms are efficient in the process of structural damage identification and detection of location, but the extracted features required for classification is hand crafted and hence as mentioned for another damage scenario, features shall be extracted again and this process is not feasible for complex structures and hence improvement or transition to another model of algorithm shall be required for superior SDD applications.

5: Machine learning based model updating methods of SDD

5.1 Model updating in SDD

Model updating is understood as the process of correction of the Finite element (FE) numerical models by extracting and processing the vibration response data from experimental structures. Natural frequencies and mode shapes are processed through modal analysis and in some situations, the numerical simulation results do not correlate with the experimental results and this introduces the concept of "inaccuracy" in numerical models. The process of model updating and it's requirement has been explained by Friswell and Mottershead [24] , where the commonly encountered modelling errors causing "inaccuracy" are classified as :

1. Model structure errors: errors occurring during the modelling of the structure and classifying the non-linear behavior.
2. Model parameter errors: errors include the unfitting boundary condition and inaccuracy in assumptions used to simplify the numerical model
3. Model order errors: arising during discretization of complex structural systems and resulting in a model of insufficient order.

Thus model updating is a way of correcting and improving the numerical models [25]. As shown in the figure 5.1, the procedure of model updating is explained, where the procedure usually begins with FE modal analysis and experimental modal analysis, where the global matrix of stiffness [K], mass [M], and damping [C] are extracted. The adaptation techniques are applied to compare the numerical and experimental models and hence if the correlation between the two models are accurate then the updating procedure is finished. After correlation, the important step is to choose the required amount of parameters for updating for which different optimization algorithms have been used till date. The purpose of model updating is to update the elemental parameters such as mass, stiffness and damping parameters of the structural model and also in some cases the individual elemental parameters such as Young's modulus of elasticity and density of the materials etc. to acquire a good correlation between the numerical and experimental result data. Thus for predictive use of the updated model, it is important to correct the inaccuracy in the modelling assumptions, which will arise due to model updating procedures.

But before updating, it is important to decide on what type of parameters shall be chosen to be updated, there are certain rules that are taken into consideration for selecting the FE model parameters that shall be updated [26]: Uniqueness: The chosen parameter values shall be unique, the chosen parameters shall not produce the same modal results. Sufficiency: In choosing the parameters, it is important to choose those parameters which are sufficiently wide to cover the real change in parameters for successful model updating. Also if too few or wrong parameters are chosen then the convergence between the experimental and analytical results shall fail and also the process of model updating shall fail.

5.2 Two main branches in model updating

After the required parameters are chosen for updating, the process is further classified in two categories:

Direct method of model updating:- This method of model updating is based on reproduction of the measured data and the model is termed as "representational". There are certain advantages and drawbacks of this method of updating such as there is no requirement of iterations in the updating process and hence the need of divergence and excessive computation are not required.[24] But since this method required accurate modelling, the natural frequencies of a structure can be accurately measured but the mode shapes are not said to be accurate in measurement as errors originating in the model shall also cause error in the chosen data for updating process and hence the inaccuracy in the mode shape measurement as commented by Friswell and Mottershead [24]. For example [27]- these methods are based on updating the measured modal data and also updating the entire structural matrices and hence the updated matrices are referred as those which are closely related to the initial analytical matrices but reproducing the measured data.

Iterative method of model updating:- The main objective of iterative based model updating method is to improve the relation between the experimental data and analytical model data. Since these are iterative based methods , hence we are allowed a wide area of choices for updating the parameters and also the concept of weighing the different data sets (experimental measured data and analytical parameter data sets).

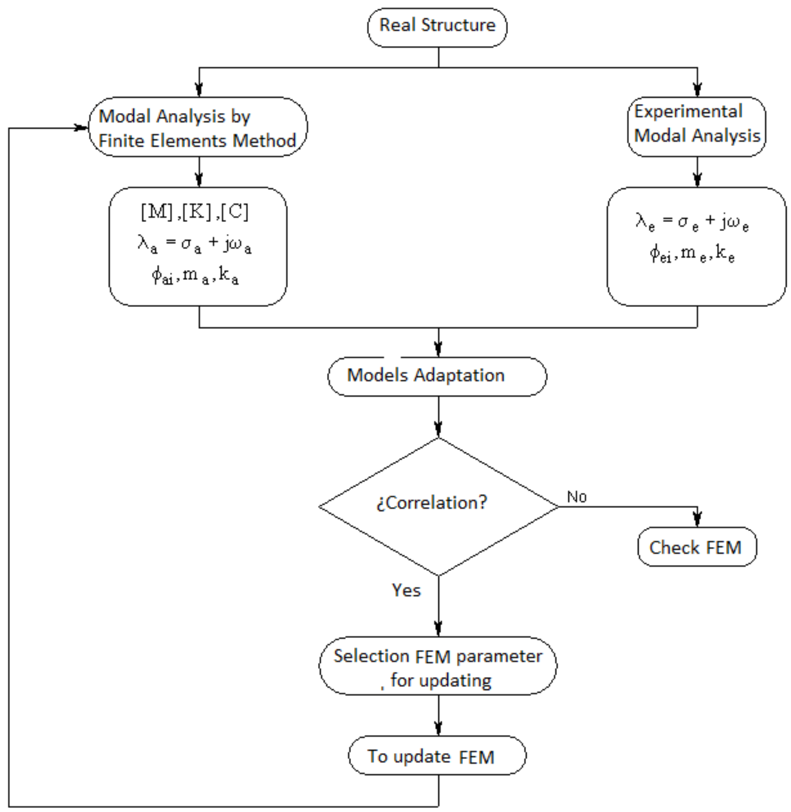


Figure 0.1 Procedure of model updating as adapted from [25]

5.3 Comparison of model updating and integrating model updating in neural networks methods of damage localization

Thus in this chapter the research studies on damage localization with model updating and integrating model updating with machine learning algorithms shall be compared and the most efficient method of damage localization shall be concluded through comparison.

In the first study, Velasco et al. [25] showed the comparison of model updating and neural network methods for damage localization. In this study, the author's proposed an iterative based model updating procedure. For the model updating, a finite element model with 20 or 40 beam elements and only vertical vibration modes were analyzed and the positions of the transducers as shown (in Fig 5.2) which is required for obtaining the experimental data has been chosen through an optimization methods of effective independence and Guyan reduction.

Firstly the experimental modal analysis was coordinated by measuring the frequency response functions when the

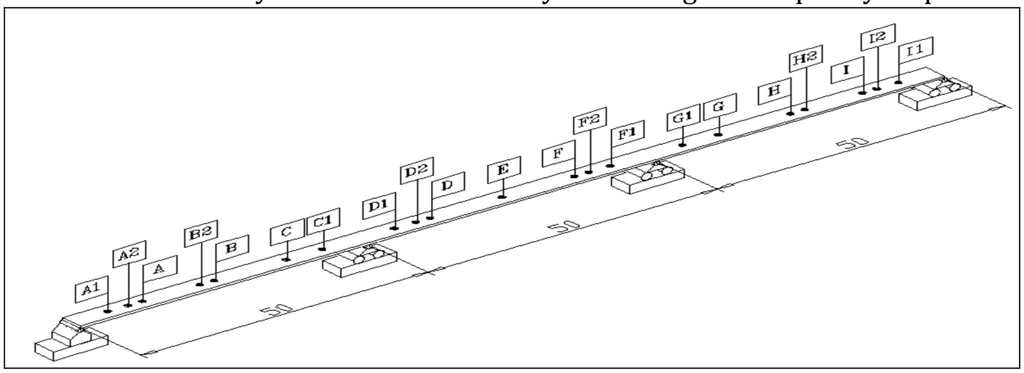


Figure 0.2 Position of the transducers and the beam elements

structure was excited by a hammer impact vibration. In the analytical analysis the natural frequencies and mode shapes were extracted .Thus as shown (in Fig 5.1), the modal result data from the experimental and analytical model were taken and compared with correlation techniques and it is shown (in Table 5.1), the vibration frequencies of the experimental and numerical model for 9 modes

Mode	Experimental Model	Numerical Model	ΔF/F (%)	Mode	Experimental Model	Numerical Model	ΔF/F (%)
1	58,9392	55,6787	5,532	**6**	312,556	311,357	0,384
2	74,0249	71,3548	3,607	**7**	508,339	500,926	1,458
3	106,222	104,195	1,908	**8**	551,695	547,01	0,849
4	227,985	222,691	2,322	**9**	618,465	630,228	-1,902
5	258,28	253,791	1,738				

Table 0.1 The vibration response (natural frequencies) comparison

3 different updating method parameters were chosen. The third model updating is conducted to identify the damage which has been introduced in the structure, the structure was intentionally damaged with damage introduced by reducing the section by 1mm height and 12.5mm length as shown (in Fig 5.3) and stiffness matrix were chosen as the updating parameters and the stiffness change in the structure indicates damage as shown (in Fig 5.4) where the process of model updating indicated the white zone as the damaged portion.

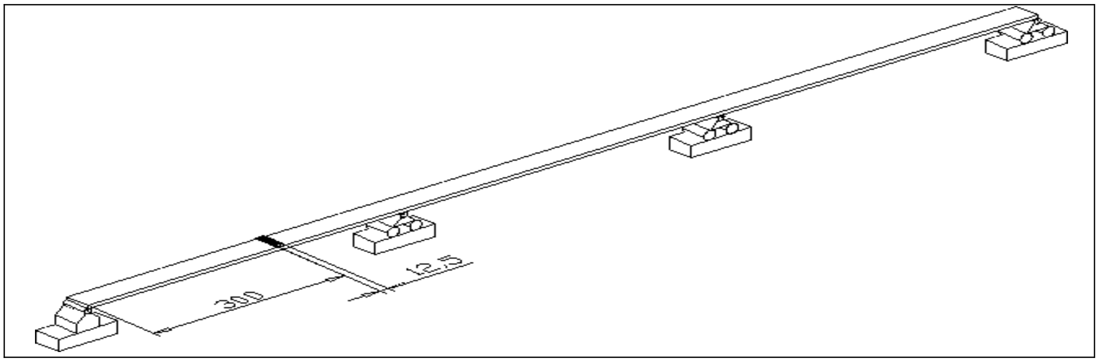


Figure 0.3 4 support damage introduction in the beam adapted from [25]

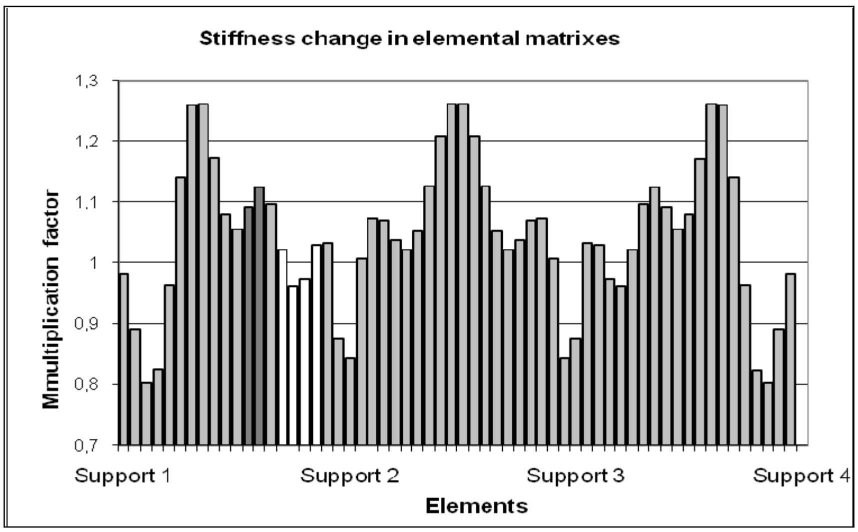


Figure 0.4 Elemental change in stiffness, white zone indicating damage[25]

Thus, the authors compared this model updating method with FE model integrating with neural networks, for the FE modelling, the beam element was chosen with length 1500mm and damage was introduced at 750 different positions of the beam and the first 5 natural frequencies were extracted from the numerical simulation model and were used as input vector data set for the Artificial neural network algorithm. Two ANNs were modelled , one a Multi-layer perceptron feedforward(MLP) with (20-2),(50-5),(20-10-10) layers and neurons and other a radial basis feedforward which depended on the transfer function. The output of the respective ANNs were the damage location, which were in the manner of pattern matching with the input set of natural frequencies. Thus the author's concluded that the even though model updating is a good technique and as compared with FE model integrating with ANNs, the damage localization procedure results were not much different but the method of model updating requires high computational time and also large number of simulations and correlation procedures to provide with a damage localization result. Hence research was conducted to combine model updating with neural nets and compare the efficiency with data driven machine learning algorithm models.

In the Second Study, Zhang et al. [28] tried to combine model updating methods with neural nets to detect damage location. The author's informed that structural health monitoring methods are classified as two: Data-driven and physics guided methods, in chapter 4, damage detection and prediction by data driven methods combined with machine learning algorithms were investigated . Thus physics guided methods are mostly based on finite element

(FE) model updating. In this study a PGML(physics guided machine learning) method was proposed by the author's, thus integrating model updating and machine learning shown (in Fig 5.5).

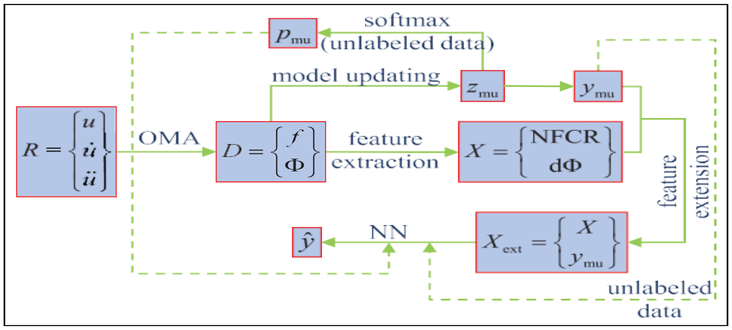


Figure 0.5 Representation of the PGML framework as used by Zhang et al [28]

Fig 5.5, explains the method of PGML used, where R is the measured vibration response, and OMA is the operational modal analysis which is the extracted natural frequency and mode shapes. Thus for feature extraction X vector set of NFCR and change in mode shape, z_{mu} is the output of the model updating process which indicates the damage extent at each damage location assumed and y_{mu} is the most probable damage location and the extended feature X_{ext} shall be used as input set for the neural networks(NN). A softmax activation function is adopted which normalizes the p_{mu} (damage probabilities) of each location that is calculated from z_{mu}. And lastly (y^) is the output of the NN. 6 damage cases were adopted with different damage extent relating to the elastic modulus change of the members. Thus in this study, a FE model, a steel pedestrian bridge was chosen and the elastic modulus of the members of the frame structure were chosen as the target of the FE model updating and the damage identification process, the results of FE model updating on a steel pedestrian bridge were incorporated to a NN model to detect the damage location. Thus the method of PGML, the most probable damage location was identified. Also an experimental study was also conducted with a three-story frame structure thus validating the effectiveness of the PGML method. Thus this study was concluded with the argument that model updating method when combined with neural network algorithms could prove as an efficient method of estimating the damage location, but in this study, the FE model updating outputs that were used as input data sets for neural nets may not be a good representation of the structural damage evaluation.

5.5 Comparison between machine learning based data driven and model updating methods of SDD

Discussion and Limitations:

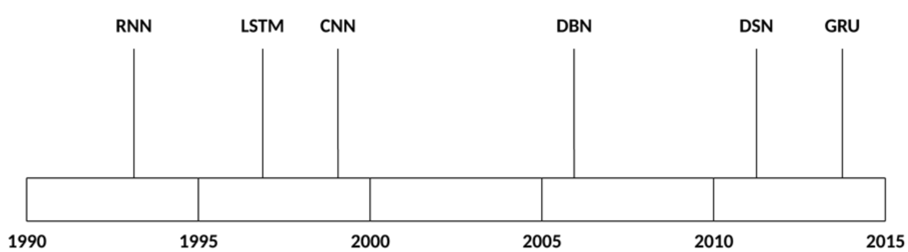
- After comparison it could be concluded that machine learning based data driven methods of SDD are more efficient than these machine learning model updating methods for structural damage detection(SDD) as the feature extraction and feature classification procedures which are mostly important for SDD applications and while in both the methods, a fixed set of hand crafted features are extracted but in model updating based methods, it is computationally in-efficient as the research studies of the latter are based on iterative neural network methods and hence until convergence, iterations are conducted and leads to high computational time.
- Although direct based methods are less time consuming than iterative methods but the algorithm of the direct method does not provide an assurance that the updated matrices (mass, stiffness and damping) will be positive[27] as negative updated values will lead to increase in process of updating.
- Also, in model-updating methods, the main limitations are that the updated parameters chosen for one structure may not be efficient for the updating process for the other civil structures.

- And in real life complex structures, the model updating process is not computationally efficient as the Finite element model of such structures shall comprise of hundreds of thousands of degree of freedom and updating of such large models are time consuming process [24]

6: Deep learning based Structural Damage Detection (SDD)

6.1 Introduction

As discussed ML(Machine learning) based data driven and model updating methods of SDD, an artificial neural network includes no more than three hidden layers with an input and output layer. Whereas DL(Deep learning algorithms) are basically an artificial neural net(ANN) with more than 3 layers and Salakhutdinov et al[29] showed that ANNs with more hidden layers have a strong learning power and the learning ability could be increased with addition of more hidden layers thus the term DL algorithms was originated. In the previous studies of Machine learning algorithms it was commented that features extracted are all hand crafted and hence one feature used for extraction may be feasible for another damage/undamaged state. Thus this problem is shown to be solved using Deep learning algorithms where the algorithm has the ability to automatically learn to extract the optimizing features from the input vector set [1]. The architecture of Deep learning algorithms are very large and over the past 20 years as shown in Fig 6.1, many architectures have evolved [30]. As shown in Fig 6.1, the DL algorithms have evolved over the past 20 years where LSTM(Long short-term memory) and CNN(Convolutional neural network) are the most used algorithms. Also Gibson et al.[31] commented on the 3 other major DL algorithm groups such as Recurrent neural networks and Recursive neural networks (RNN) and Unsupervised pre-trained networks(UPN) which are further classified as Autoencoders, Deep belief networks(DBNs) and Generative Adversarial Networks(GANs). The study of such DL algorithm networks on Structural damage detection(SDD) have been conducted by Avci et al[1] and the author's commented on the applications of Unsupervised pre-trained networks specifically Auto-encoders and Convolutional Neural Networks on SDD.



Architecture	Application
RNN(Recurrent neural network)	Speech recognition, handwriting recognition
LSTM/GRU networks	Natural language text compression, handwriting recognition, speech recognition, gesture recognition, image captioning
CNN	Image recognition, video analysis, natural language processing
DBN(Deep belief networks)	Image recognition, information retrieval, natural language understanding, failure prediction
DSN(Deep stacking networks)	Information retrieval, continuous speech recognition

Figure 0.1 Architecture and applications of various DL algorithms over the years, adapted from[30]

Hence this study shall also focus on introducing only CNNs and commenting on the various applications of CNNs in SDD but an important condition for efficient performance of CNNs are the availability of large training data sets, thus in this Chapter, the applications of Generative Adversarial networks (GANs) in creating pseudo images of damaged scenarios for use as training data shall be shown and commented on how using GANs and creating simulated training data sets effects the efficiency of the CNNs.

6.2 Convolutional Neural Network (CNN)

Over the years, there has been an increasing interest in deep learning and the most recognized algorithm among a series of deep learning algorithm models are CNNs [32]. CNNs are a class of deep learning models composing of multiple building blocks like the convolution layers, pooling layers and fully connected layers, where convolution and pooling layers performs the feature extraction process and the fully connected layer performs the mapping of the extracted features to the output layer (process of classification)[33]. A convolutional layer is an important layer of a CNN , and a convolution is carried out for feature extraction where a small array of numbers(in digital images, the pixel values are represented as 2D grid of array of numbers) as shown in Fig 6.2 called Kernels are applied across the input set , which are further

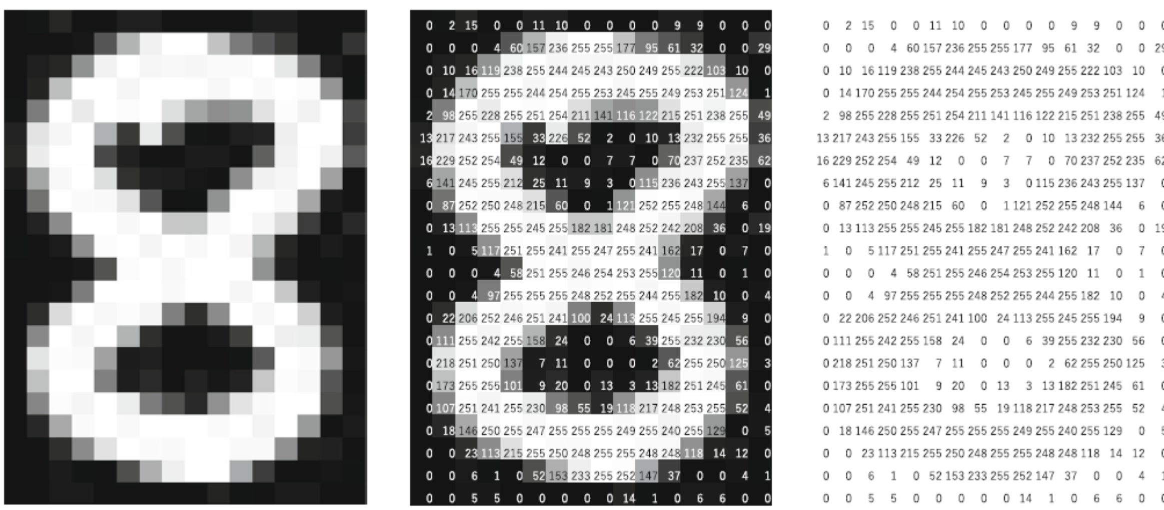
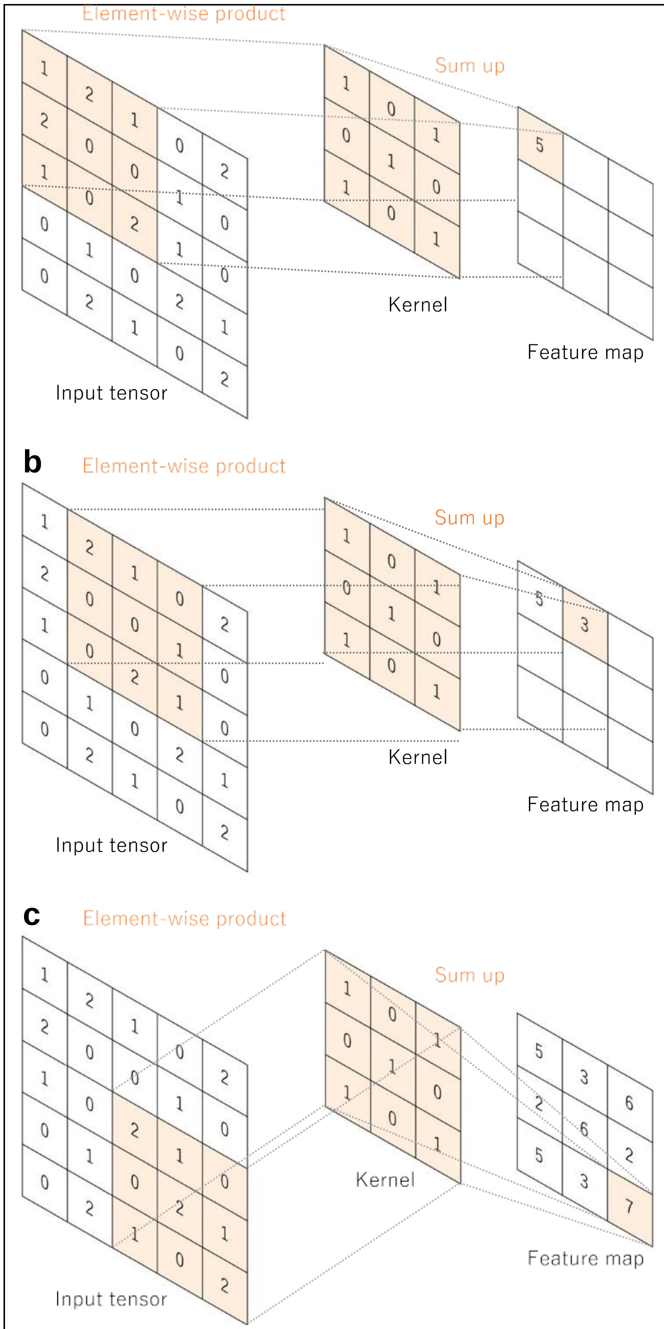


Figure 0.2 The matrix on the right contains numbers between 0 and 255 where each corresponds to the pixel brightness in the left image; both are overlaid in the middle image, adapted from [33]

an array of numbers called Tensors. Kernels are grid parameters for optimal feature extraction process and whose size is dependent on the size of the input tensor set, usually 3x3, 5x5 or 7x7 are selected. Also in 2-D images, the convolutional filters has a third dimension shown as 3x3x1(for example). [34, 35]. An example of a convolution procedure is shown in Fig 6.3, where



Yamashita et al[33] explained the process of convolution as an element dot product between each element of the kernel and the input tensor is calculated at each location of the tensor .The summation is obtained at the output tensor set called as feature map.

- This similar process is repeated with multiple kernels to simulate an arbitrary number of feature maps as shown in the Fig 6.3. Thus representing the different characteristics of the input tensor set.
- A process of padding [36,37] is usually applied where rows and columns of the input tensor set are filled with zeros to fit the centre of a kernel set on the outermost element and hence keeping the same in-plane dimension through the convolution operation.
- Another term of stride value[33,35] is used which is the distance between two successive kernel positions. For example a stride value of 1 or 2 means the kernel column or rows shall move by 2 units over the input tensor set
- A pooling layer is a typical down-sampling operation, consisting of max pooling, global average pooling[33,37].
- The final layer of convolution is fully connected layer where the activation functions(non-linear such as rectified linear unit ReLU) are used to map the input features to the output tensors through a system of weights[33]. The transformation to 1D array vector set of numbers take place where every input is connected to an output value by a learnable weight factor.
- Softmax activation function is usually applied to the last layer of the multiclass classification process thus normalizing the output real values to target probability values ranges between 0 and 1[33].

Figure 0.3 Example of a convolution procedure with kernel (filter/convolution filter) of 3x3 and without padding and stride value of 1, adapted from Yamashita et al.[33]

6.3 Advantages of Convolutional Neural Network

CNNs are successful due to certain advantages it incurs over machine learning algorithms:

1. CNNs have the ability to combine the process of feature extraction and classification into a single learning body and the algorithm is capable of automatically processing the feature extraction.

In a study by Martel et al[38], the author's proposed a Deep CNN algorithm for SDD, operating on images which were generated from the structure's transmissibility functions(TFs). In structural vibration analysis, TFs are defined as the ratio in the frequency domain between two responses when excited by a force(applied). TFs were obtained from experimental and numerical models of the proposed structure. In this study, Deep CNN based process was compared with a shallow multilayer perceptron (MLP) on a structural beam structure as shown in Fig 6.4,

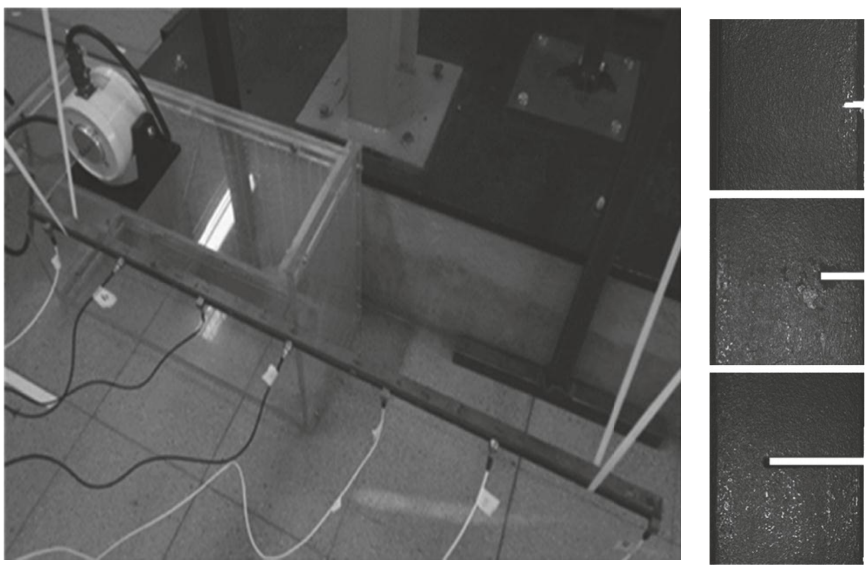


Figure 0.4 Experimental test on a beam with different damage scenarios introduced by way of saw cuts, adapted from [38].

and the architecture of the MLP layer were same as the CNN layer but without the convolutional layers. Thus a MLP layer consisted of one hidden layer of 1024 units and an output layer of total units as damaged elements. After comparing the two model algorithms as shown in Fig 6.5, CNNs were concluded to show greater damage prediction accuracy as compared to the MLP models as it is shown in the above figure apart from CNN and MLP model 2, model 1 and 3 of MLP show less accuracy in predicting damage location as compared to CNN model. Thus CNNs also have the advantage of automatic feature extraction and hence manual extraction as applied in MLP model is time consuming and not efficient. Apart from these, there are other advantages of CNNs over MLP as such as:

2. CNNs have the ability to adjust the input data set size to a different size and can compute large inputs with greater computation efficiency [39].
3. Small transformations such as translation, scaling, skewing and distortion in the input data set do not affect the CNN model algorithm [1].

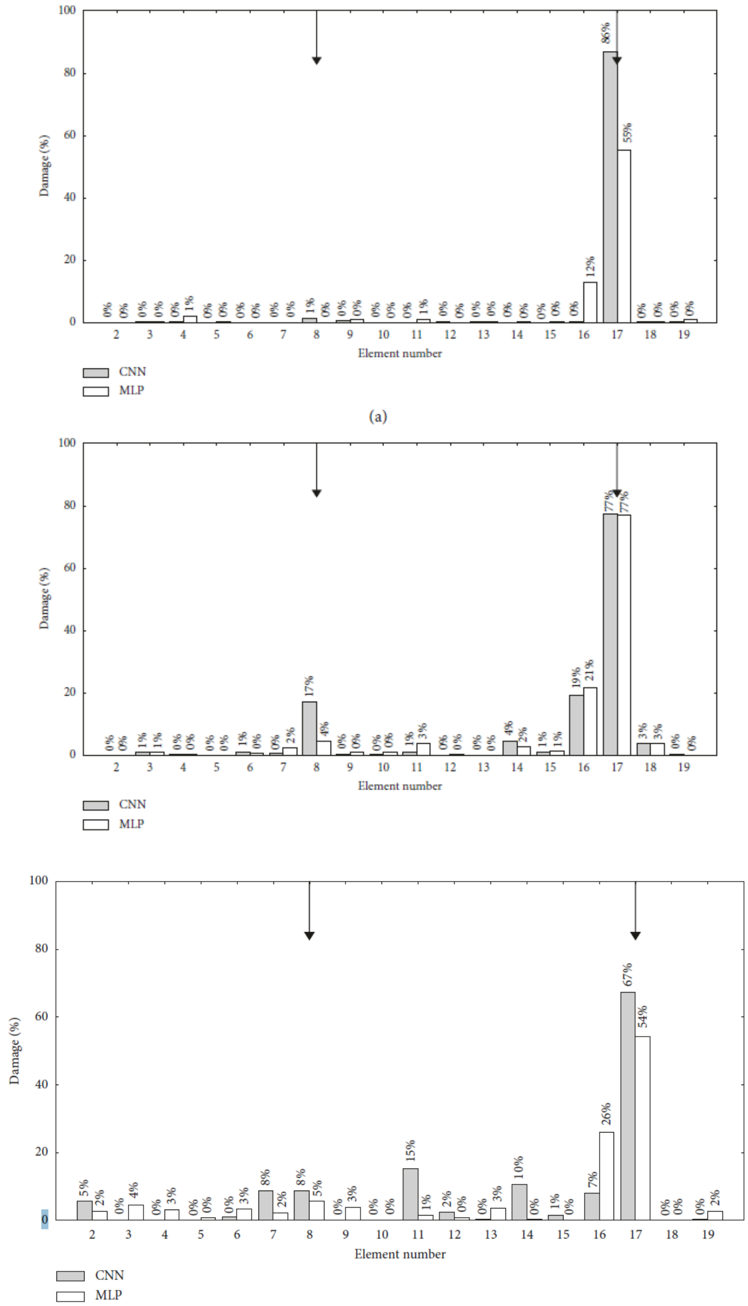


Figure 0.5 Comparison of CNN vs MLP for different CNN and MLP models (representing damage scenario 3), adapted from [38].

6.4 Applications of 2-D Convolutional Neural Network

With the efficient learning nature of the CNN models, it has been used for various vibration-based SDD applications.

For example in a study conducted by Fadali et al[39], where the author's had proposed a CNN based SDD method, on an idealized two-span frame of a cast in place, post-tensioned, continuous reinforced concrete box-girder bridge as shown in Fig 6.6. 4 damage levels were introduced on the structure from "no-damage" to "extreme damage" and the vibration responses were measured by a number of accelerometers for each damage level and later data processed were linked together in the form of a single 2-D matrix. This input data-set were used to train a CNN of 5 convolution and 4 fully connected layers. 14 accelerometers measured the response from a base excitation of the model structure with different intensities. The formation of various damage states in the bent columns were recorded. A feature matrix of (610x14) was formulated which later was formed as a feature vector of (8540x1). 2-D CNNs were used and each acceleration response were formed into a (122x70) matrix and fed as CNN input image. The pooling layer taking a region of (2x2) did compute a maximum value repeating five times and the output of the last pooling layer was formed into a column vector and used as input for the fully connected layer. After 5 convolutions, the dimensions were reduced from (122x70) to (4x32) and the dimension of the fully connected layer reduced from (128x1) to (60x1). For training of the CNN, (out of 48 shake table measurement result sets), 40 were used and rest 8 were used for testing. Thus the author's concluded by showing the efficiency of the proposed CNN model in quantifying the damage condition of the bridge directly from the measured acceleration response.

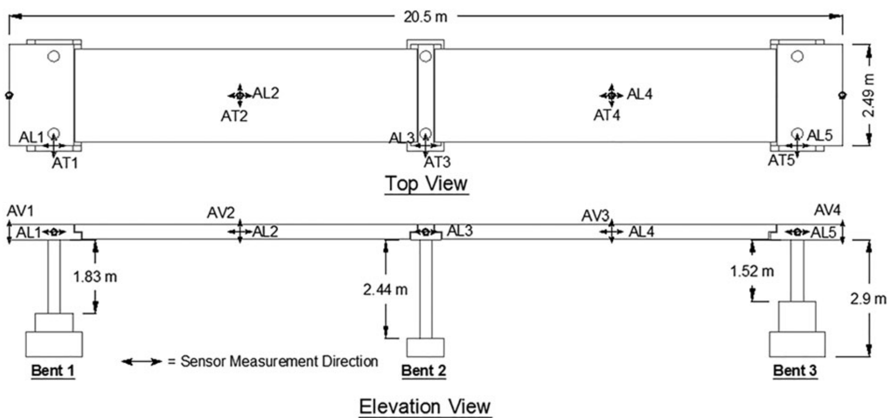


Figure 0.7 Model structure used by Fadali et al[39]

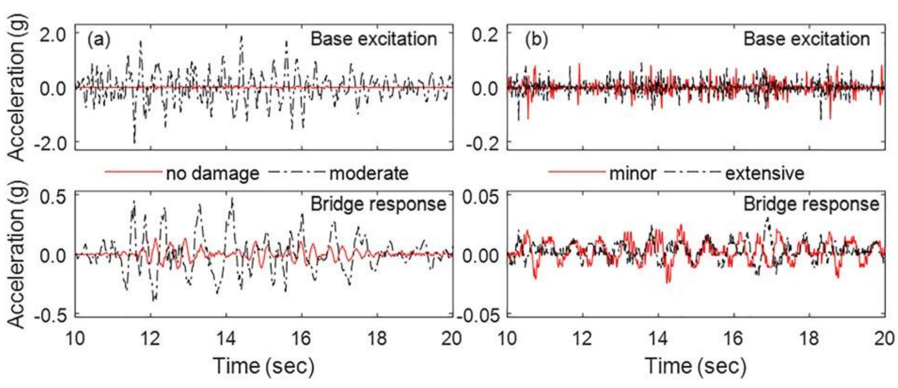


Figure 0.6 Sample acceleration response history adapted from [39] (a) earthquake: shake-table experiment Ids 12 (no damage) and 19 (moderate); (b) white-noise: shake-table Experiment Ids WN1718A (minor) and WN2021A (extensive)

The next study shall comment on the applications of an **Unsupervised CNN model network**, proposed by Cha et al[40]. In **supervised learning models**, the data from the undamaged and damaged states are required for training but in **unsupervised model**, the data from the intact state is only required, which is true for all real life structures as the model data for damaged states are not available for training. The author's proposed an approach in unsupervised learning capable of learning to extract the features from the raw vibration signals. For this approach, a lab scale experimental steel bridge was modelled with 10 accelerometers as shown in Fig 6.8. The vibration response was recorded by the accelerometers for an impact by a hammer, and in this study only the vertical direction was considered for measuring the response. The damage scenarios were introduced by way of loosening the bolts at one specific locations adjacent to an accelerometer. After acquisition of the vibration responses, the data was pre-processed using Continuous wavelet transformation and Fast Fourier transformation and thus, the 1-D signals were transformed into a 2-D data matrix and used as input set for the CNN. The unsupervised CNN model consisted of 2 CNN layers and 2 pooling layers with one fully connected layer. For the novelty detection process in an unknown testing dataset such as for an Unsupervised model, OC-SVM(one class support vector machine) classifiers were used and shown in Fig 6.9, the damage detection with OC-SVM and utilizing the extracted features from the acceleration response signals. Two types of damage sensitive features were extracted from the unsupervised CNN with the intact/undamaged state matrix were used for training the CNN. Data matrix of 50x1000(50 rows corresponding to scale range and 1000 columns corresponding to frequency ranges) were calculated after data pre-processing and into 2-D feature vectors, where one vector corresponds to one accelerometer in one test. Thus the author's concluded with commenting on the efficiency of the unsupervised training of the CNN model to locate the damage location corresponding to the accelerometer location. Though this method was successful, but more damage scenarios were needed to be introduced and checked.

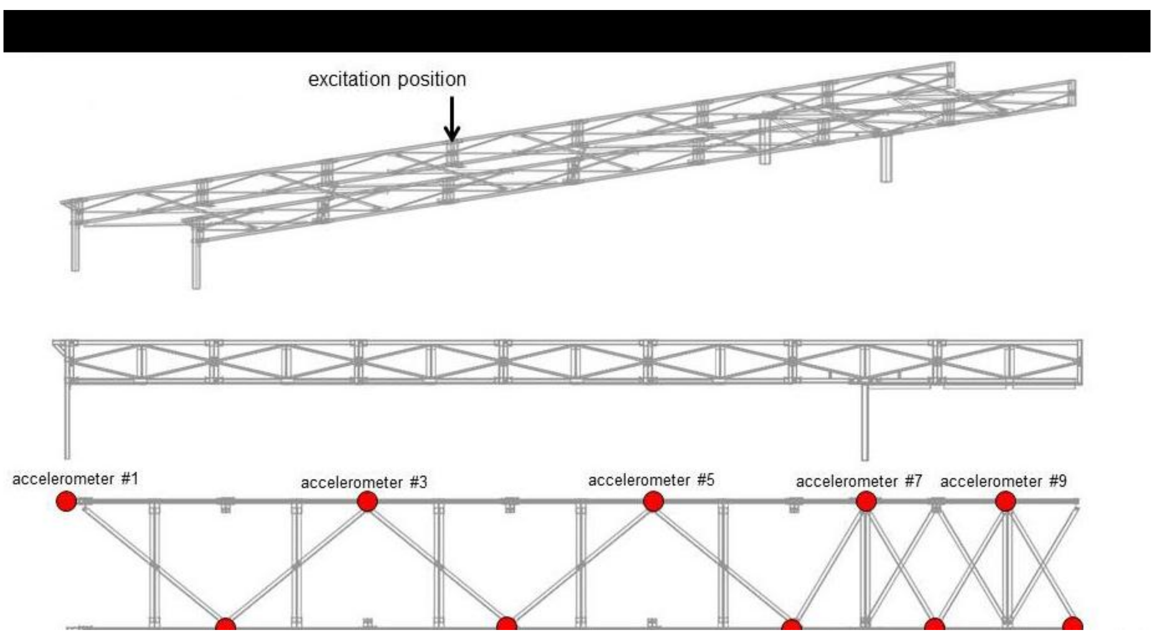


Figure 0.8 Model structure and locations of the accelerometers, adapted from[40]

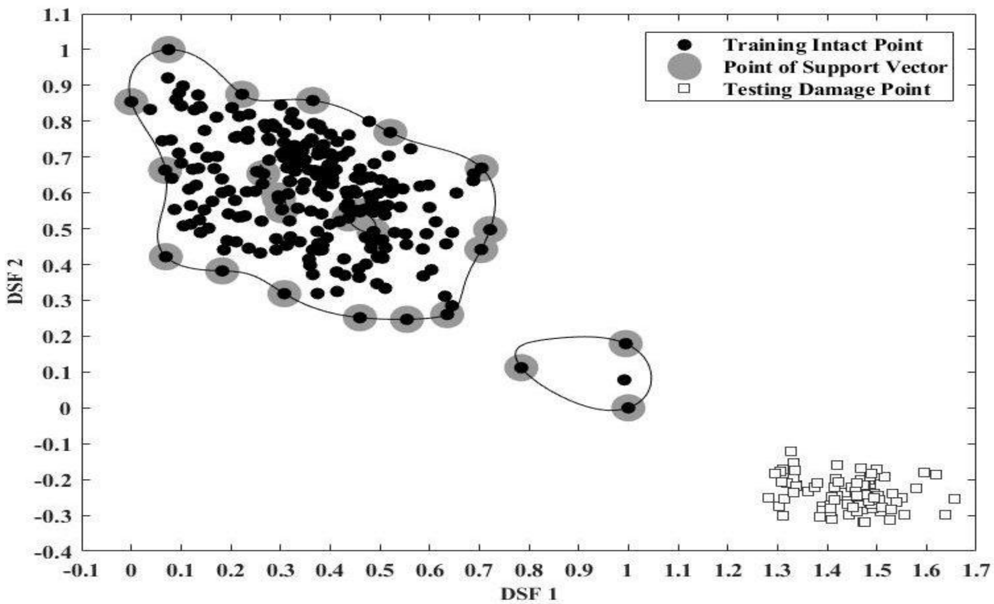


Figure 0.9 Detecting damage at accelerometer location with OC-SVM, adapted from[40]

Similar there are some other applications of CNNs in the form of using 1-D vibration signals as input set and referred as 1-D CNNs.

6.5 Applications of 1-D Convolutional Neural Network

As the efficiency of CNNs were discussed to automatically detect the features and classifies in a single body, there are also certain applications of 1-D CNNs which were firstly used in ECG monitoring, Gabbouj et al[40] where the author's used 1-D CNNs for classifying long ECG records of each patients and showing the superior classification performance of the 1-D CNNs. Following this study, Avci et al[42] conducted an experimental study on a grandstand frame structure with uniaxial accelerometers for measuring the vibration response under 31 damage states. The 1-D signal responses measured at each location of the accelerometer were used to train the 1-D CNN. A complexity analysis was conducted to measure the computational time or measurement sessions for the process of 1-D CNNs in this study. The measurement data for this study was published online [43] with the source code of the 1-D CNN model algorithm.

Also a similar study was conducted by Avci et al[44] where tri-axial accelerometers were used to measure the vibration response and estimate the direction in which the damage sensitive features are more distinct. Shown in Fig 6.10, the position of the tri-axial accelerometers for measuring the responses under the damage states introduced. The 1-D CNNs trained in this study consisted of two CNN layers with four neurons and two MLP layers with five neurons. Though the efficiency of the CNN model was shown to be superior in identifying and locating the damage from the raw vibration signal responses but it was concluded that the process of data generation from the vibration response to train the 1-D CNNs lead to a large number of measurement session or computational time.

Figure 0.10 The model structure and the accelerator position, as adapted from [44]

Thus in the next study by Abdeljaber et al[45] , developed an adaptive 1-D CNN damage quantification approach and tested on a benchmark study [46]. 37 undamaged and 112 damaged state frames were selected to train each 12 CNNs , one CNN for each accelerometer position. The average time for BP iteration per state frame were 150 msec (approx.) and total training time required were 42 sec for all the CNNs. Through MATLAB code the vibration responses were arranged in frames and then normalized and used as input set for the 1-D CNN shown in Fig 6.11,

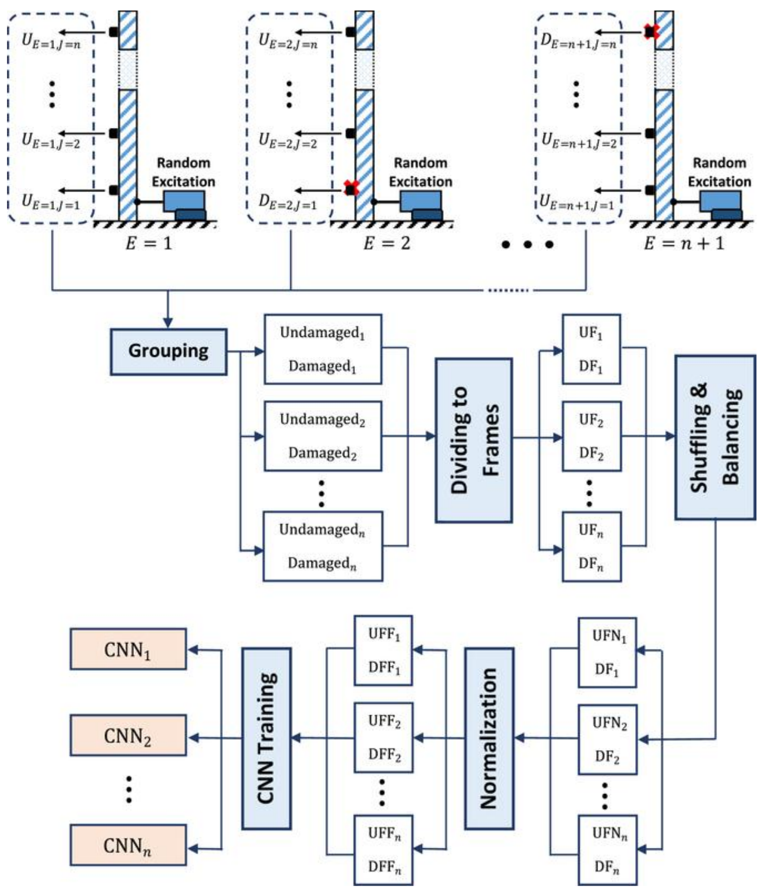


Figure 0.11 Data generation and the training process of the CNN, with the damaged joints marked as red-cross, adapted from [45]

and the classifier was used to estimate the Probability of Damage (PoD_i). The time required for computing the PoD_{avg} was 60 msec for 12 acceleration signal responses. Thus it was concluded that the computational time for the adaptive 1-D CNNs were 500x faster than the previous models. Thus the studies on 1-D CNNs for Structural damage detection (SDD) have shown that the CNN model is able to learn and distinguish complex data directly from the raw vibration signals and also the compact 1-D CNNs were proven to be able to accurately distinguish complicated data from the acceleration time-history responses[1] , samples of the signals are shown in Fig 6.12.

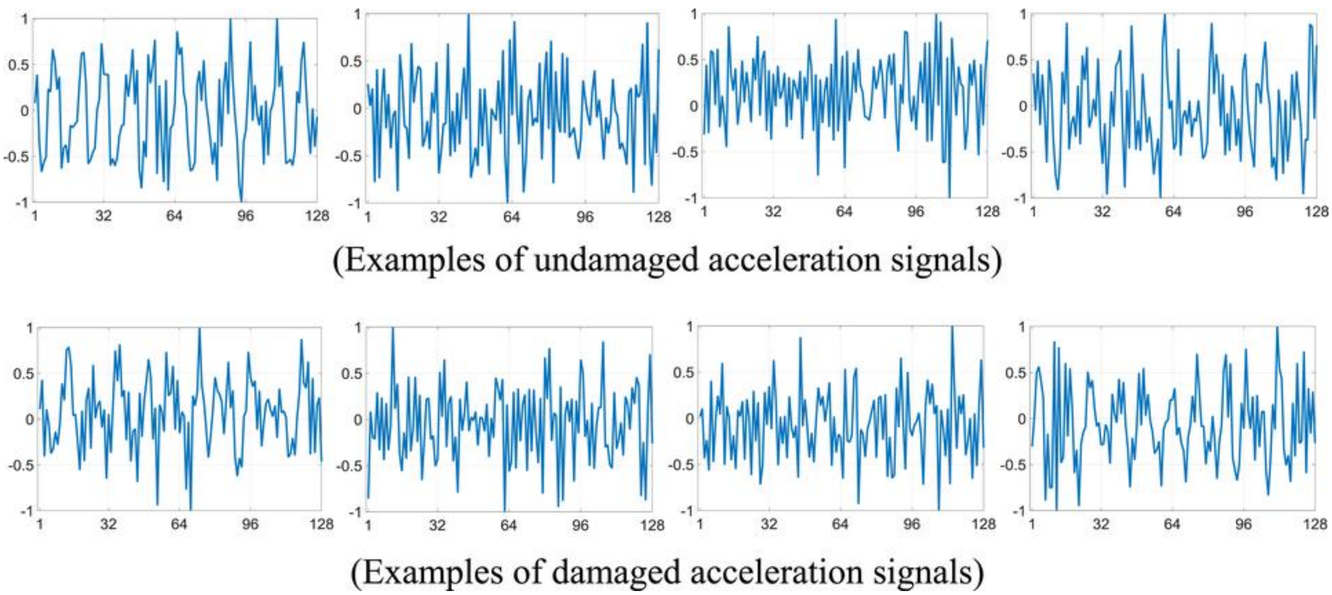


Figure 0.12 Sample accelerometer signal responses acquired, adapted from [42]

6.6 Comments on 1-D CNN vs 2-D CNN for SDD applications

As discussed above the efficiency of the two CNN models, the comparison of 1-D CNN vs 2-D CNN have been discussed by many researchers till date, and both the models have certain advantages over another such as

- 1-D CNNs require low computational time as shown in studies [42,44,45], as the feature extraction and classification step is fused into a single body.
- In 1-D the BP and FP operations requires low and simple array matrices and the convolution process requires (few hidden layers and less neurons) but 2-D Convolutions requires large array matrices and the training is conducted on special hardware such as GPU farms[47].
- Even though 1-D CNNs have been proven superior in SDD applications for automatic extraction and classification from 1-D vibration signals, but in real complex structures, there may be measurements from multiple sensors over time and hence in 1-D CNN applications these measurement data could be linked together and formed as a single measurement which shall increase the dimension of the input signal thus affecting the CNN model performance [39].
- For example in a study conducted by Fadali et al[39], the size of the feature matrix was 610x14 and feature vector was 8540x1, which would have not been efficient if 1-D CNN model would be used .

Thus, even though the two models have their advantages and dis-advantages, it can be concluded that both the models are equally efficient and there is a further need for a study to optimizing the computational time of 2-D CNN and also with increase size of input matrix, the performance of 1-D CNN shall not be effected.

6.7 Obtaining training data in absence of damage data for training

Till now in every research study conducted, the importance of availability of training data has been mentioned and since ML algorithms or DL algorithms (including CNNs) are data hungry, they learn to adapt and improve their efficiency with the amount of training provided to the model algorithms with large amount of training data. And since this dissertation study has shown how CNNs are more superior than ML algorithms, and that training data are required for CNNs model, but pre-damage and post-damage data are not possible to obtain, thus researchers have taken the advantage of certain network models to obtain the training data such as Generative Adversarial Networks (GANs). Generative adversarial networks were introduced by Goodfellow et al.[48], where the author's constructed a training data set on limited test data through the training of two neural nets (the generator and the discriminator). GANs have been utilized for procuring simulated training data in various damage detection fields of civil engineering , for example a study by Maeda et al.[49], GANs were used to generate a pseudo-image from a real damage image as shown in Fig 6.13.

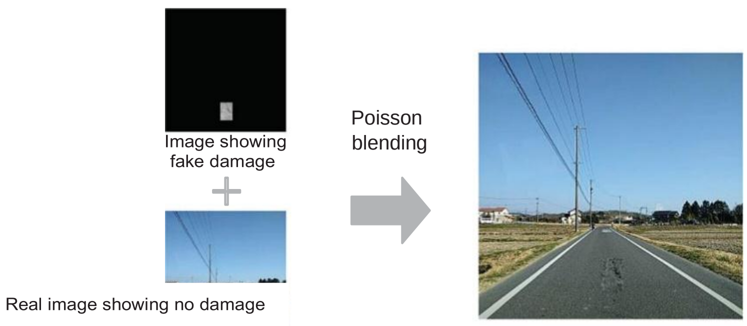


Figure 0.13 Generation of pseudo-image for construction of training set, adapted from [49]

Similarly in a study by Zhang et al.[50] , 1-D CNNs were modelled for SDD on a steel Warren truss bridge and for overcoming the challenges of limited training data or monitoring data, GANs were used. The generator was used to generate synthetic data from the real data and the discriminator thus tries to distinguish between the two. Thus the synthetic data generated by this process closely resembles the real data. The process is shown in Fig 6.14, where two stages of process, the data generation process of the available monitoring data in time domain transformed to frequency domain and generative neural network constructed to produce new data sets with random noises. Second process of constructing a discriminative neural network aiming to find effective features for structural identification under high noise by comparing the real and generated data. Thus GANs have been proved efficient and successful in providing the CNN models with synthetic training data for increasing the performance of the CNN and providing a way of solving the problems of acquiring real time damage data.

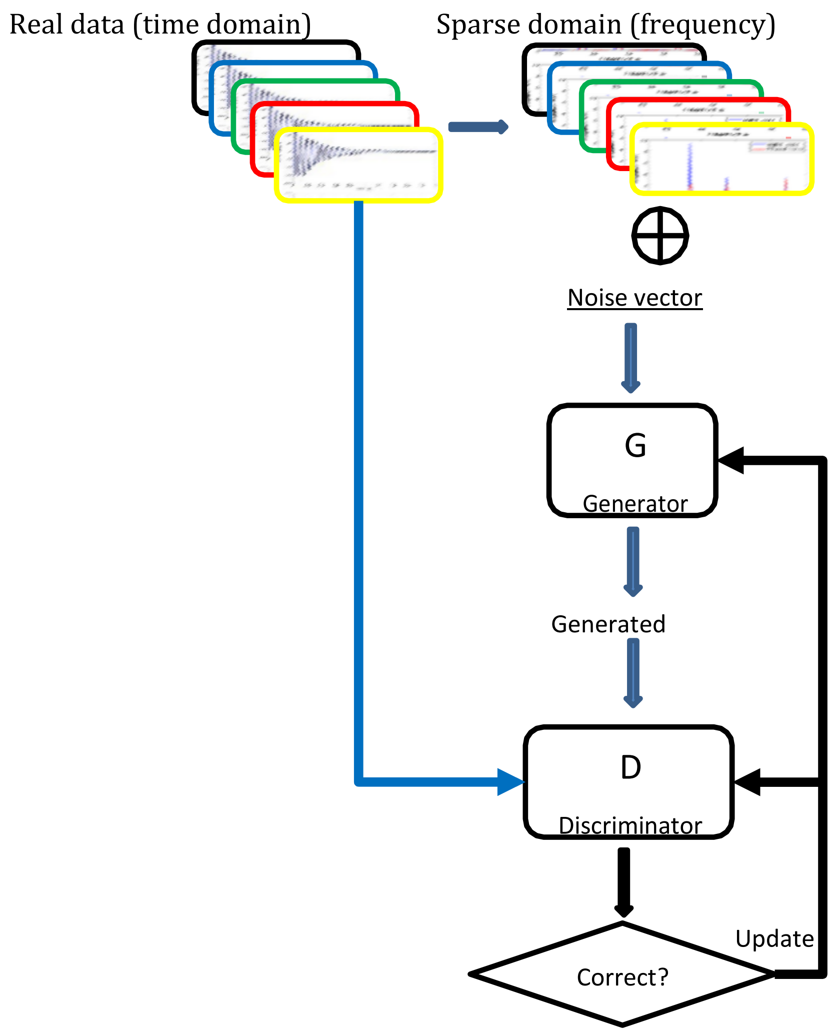


Figure 0.14 Proposed GAN network used by Zhang et al.[50]

7: Conclusions and Discussion and Recommendation for future work

Structural damage detection, an important application of Structural health monitoring has become a constant research topic and finding ways of minimizing the computational time for damage identification process has been the main objective of all the research studies. This dissertation study has created a branch of SDD by showing the traditional methods of damage detection and giving a background information on Artificial Intelligence (AI) and Machine learning(ML) based data driven and physics based Model updating and Deep learning(DL) methods and commenting on the ML based studies published on parametric and non-parametric based SDD applications and also studies on ML based physics based model updating methods and thus comparing the two studies with Shallow and Deep CNNs model of vibration based damage detection. This study has concluded by providing the reasons for transition from ML to DL algorithms for SDD and a range of research studies have been analysed and reviewed in detail, and particular importance have been given to the feature extraction process, for example the features extracted from the raw vibration signals and thus classifying the extracted features. The studies were analysed in terms of these two process and experimental/numerical and analytical models were used for analysis.

Thus based on the literature review that has been conducted in this study, the following conclusions are summarized:

1. ML based methods of SDD are composed of two tasks: feature extraction and classification, thus these make majority of ML methods more advantageous than traditional damage detection methods.
2. In vibration based methods, the extracted features or damage sensitive features such as natural frequencies and mode shapes and damping ratios are not an effective choice as they are mostly affected by environmental factors such as change in temperature and other moisture conditions.
3. As shown in the comparison of the research studies of ML algorithms model of parametric and non-parametric data driven methods, the extracted features are mostly hand-crafted and hence the extracted features have to be changed for a different damage or undamaged scenario introduced and also there have not been an optimum choice for the number of extracted features.
4. In ML based physics based , a fixed set of hand crafted features are extracted but in model updating based methods, it is computationally in-efficient as the research studies have suggested for iterative neural network methods that until convergence, iterations are conducted and leads to high computational time.
5. Thus Shallow and Deep CNNs (1-D and 2-D) were introduced by the researchers to solve the problem of hand crafting the features, such as in 2-D (Deep) CNNs, the feature extraction and classification process is combined in a single body and hence the features are automatically extracted by the convolutional filters and classified by the algorithm, similarly in 1-D (Shallow) CNNs, the features are automatically extracted from the raw vibration signals and hence any new features can be easily extracted from the input sets.
6. Lastly, the importance of having or acquiring data for training has been mentioned in all the studies reviewed for this study, as the data which are acquired each day are from the same intact / undamaged structure and thus the data for other damage scenarios are not available.
   Also acquiring data from numerical model results could be used for training but in some cases the data acquired are not easy to simulate the complex behaviours of the structure and thus the difference between the real behaviour of the structure and the numerical result leading to wrong results of identification of the damage.
7. Hence, GANs were used to produce pseudo-images of damage data or simulated images of real data through their network which have close accuracy with real data and hence can be used for training the CNNs.
8. This study can be concluded by providing views on conducting more research work in acquiring of data for training the CNN algorithms and also conducting research in the possibility of training the classifiers with real-life data obtained from the intact structure and using damage data from FE model or through experimental but keeping the error factor of difference of obtaining the data between real-life and FE model or experimental.

Conflict of Interest

"The author declare no conflict of interest".

Acknowledgment

The author wish to thank University of Leeds for providing help in procuring the research case studies. The author would like to thank Dr Nikolaos Nikitas from the School of Civil Engineering, University of Leeds for mentoring in this research study.

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