Title: A review of bridge health monitoring based on machine learning

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Abstract

This paper reviews structural health monitoring (SHM) techniques of bridge structures based on machine learning (ML) algorithms. Regular inspections or using non-destructive testing are still the common damage detection methods; they are susceptible to subjectivity, human error, and prolonged duration. With emerging technologies such as artificial intelligence (AI) and the development of wireless sensors, SHM has shifted from offline model-driven damage detection to online/real-time data-driven damage detection. In this paper, both supervised and unsupervised ML algorithms are studied to determine which of the latest methods would be the most suitable and effective to be used for the SHM of bridge structures. This review paper investigates recent studies on data acquisition, data imputation, data compression, feature extraction, and pattern recognition using supervised/unsupervised ML algorithms.

1. Introduction

Civil structures particularly bridges undergo harsh environmental loadings and impacts, hence, are subject to deterioration and damages such as cracks, corrosions, etc (R Farrar & Worden, 2007). If the damage is not identified and maintained, it may cause component failure or even the collapse of the structure (Flah et al., 2022). To remedy this issue, SHM has emerged as a powerful tool to identify such anomalies before any potential failure and inform asset owners for more efficient decision-making. This aids towards strategized cost-effective maintenance (Chen, 2018). Most SHM systems are composed of four main components: (1) data collection, (2) data processing, (3) damage identification strategy, and (4) decision-making (Malekloo et al., 2021). Figure 1 showcases the components of SHM which will be discussed in this paper.

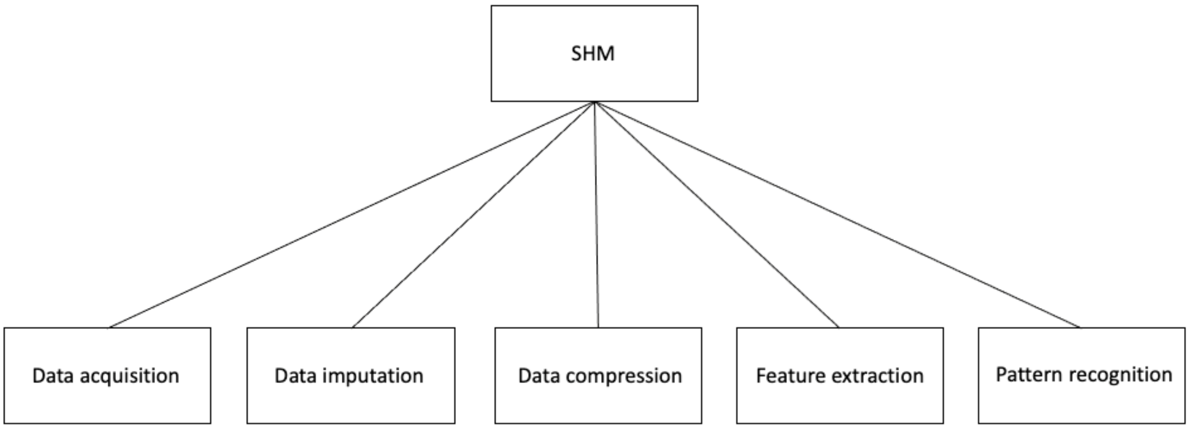

Figure 1. Components of SHM reviewed in this paper

Regular inspections or using non-destructive testing are some old-fashioned examples of damage detection methods and are susceptible to subjectivity, human errors, and prolonged duration (Hull, 2002). In the case of complex structures, particularly areas which are hard to reach, these techniques would be ineffective (Farrar & Worden, 2007). Hence, numerous offline/in-situ vibration-based methods were developed to identify damage in large-scale structures, where the structure is excited by an impact hammer, dynamic shaker, or controlled moving vehicle (Brownjohn, 2007; Caicedo & Dyke, 2005; Farrar et al., 2007). However, these methods require prior knowledge of the damaged structure, and a high-fidelity model of the structure (model-driven methods) is required to simulate the damaged state of the structure (Azimi et al., 2020). Additionally, these methods are incapable of continuous monitoring of the structure, to accurately estimate the initiation time of the damage, damage progression, and determine the remaining lifetime of the structure (He et al., 2009). With emerging technologies such as artificial intelligence (AI), SHM has shifted from offline model-driven damage detection to online/real-time data-driven damage detection (Rosafalco et al., 2021). In this approach, SHM uses the real-time vibration measurement of the structure under operational loadings without any prior knowledge of the damaged structure to detect any anomaly or malfunction in the performance of the structure through unsupervised machine learning algorithms (Pimentel et al., 2014). If any damage is identified, a decision is then made on offline detection and maintenance methods.

Online data-driven SHM relies on statistical pattern recognition of the real-time measured vibration data with the use of unsupervised machine learning, meaning that *training* the pattern recognition model, i.e., identifying the models' parameters, needs only unlabelled data, i.e., raw data. Supervised ML techniques have also been explored in the field of bridge SHM, with supervised ML the data used to train the pattern recognition model need to be labelled meaning the data for both healthy and damaged states need to be available. This paper investigates the use of supervised and unsupervised ML techniques in structural health monitoring. This paper reviews the use of machine learning in different components of an SHM system: section 2 focuses on data acquisition, section 3 discusses data imputation, sections 4 and 5 talk about data compression and feature extraction, and section 6 looks at pattern recognition. Many machine learning methods are reviewed, and their pros and cons are discussed.

2. Data acquisition

This section refers to how machine learning has been used to collect data efficiently. A robust SHM requires a reliable and accurate set of response data. This can be achieved through optimal sensor placement (OSP) (Sun & Büyüköztürk, 2015). Genetic algorithm (GA) is a powerful tool to find OSP. GA is a search heuristic where it finds solutions, meaning an optimal sensor location, by creating small changes in the current solution (Leung et al., 2003). This method is based on Darwin's theory of evolution; the population size represents the number of solutions. Each possible solution is represented by a vector, consisting of a set of parameters. It is encoding the placement of sensors in the same way chromosomes encode genetic information. The solutions' fitness value is evaluated using a fitness function meaning a bigger fitness value suggests a better-quality solution. The fittest solutions go to a "mating pool" where each act as a parent and every two parents generate two offspring. Figure 2 represents a flow chart of how GA works.

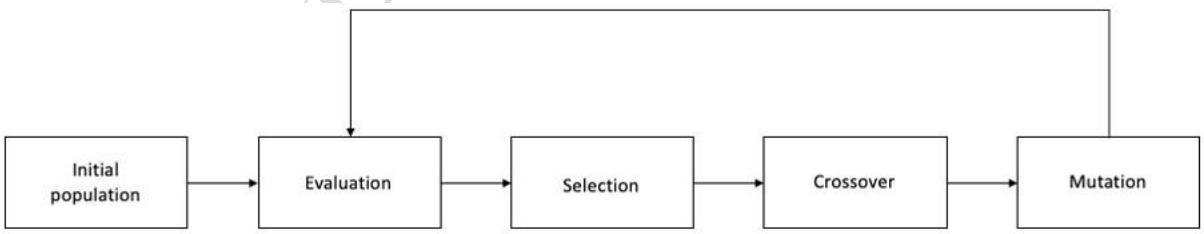

Figure 2. Genetic algorithm

The offspring is expected to have better qualities than the parents. GA can take a large number of generations to find the global optimum and it can also face convergence problems. Banik & Das (2020) used the learning advantages of an artificial neural network (ANN) to overcome the drawbacks of GA's convergence problems. They used a feedforward backpropagation neural network with supervised learning where the design variables and fitness values gathered from GA were used as the target and input vectors respectively. To put this model to test, a first-generation benchmark model of the Bill Emerson Memorial Bridge located in Cape Girardeau, Missouri, USA was utilised. This bridge has a length of 1205.8 m with two towers and 128 cables. The model resulted in a fair distribution of sensors with greater fitness value and improved convergence. Therefore, to utilise GA for Optimal Sensor Placement, an accurate finite element (FE) model is required, and the success of the model depends on the parameters and design variables chosen for the ANN such as network architecture, training algorithm, performance function, transfer function, etc.

3. Data imputation

A high-quality dataset is essential for an SHM system to perform efficiently. Not all data gathered by the sensors are always suitable to be used, this could be due to many reasons such as sensor misplacement or malfunction (Z. Chen et al., 2019). In some events when the gathered data is unusable, it gets decimated. In some cases, there are missing trends in the data which the data gets imputed and recovered. Several ML techniques are used for replacing the missing data. It is known as data imputation. Bayesian temporal factorisation (BTF) models are great for high-dimensional time series analysis (X. Chen & Sun, 2021). However, this method is not efficient since the model needs to be retrained with every new dataset. To overcome this, Ren et al. (2020) implemented an incremental approach to the Bayesian temporal factorisation model, in which the model is efficiently updated with the new data. This method was successfully tested to impute strain and temperature records of a concrete bridge. Siahkoohi et al. (2018), used generative adversarial networks to reconstruct sub-sampled seismic data. To implement this method, it is assumed the training data is available with a percentage of the shots to be fully sampled. The model created was an adaptive non-linear model and due to the data-driven nature of the method, high-quality reconstructed slices were generated. These data imputation techniques can be reliably used only if the available data is of high quality and the missing data is not over a continuous period (e.g., data missing for a day or consecutive days).

4. Data Compression

Data required for SHM is generated by various sensors with different sampling rates. Environmental and operational factors (EOFs) such as temperature and moving traffic add to the dimensions of the dataset (Jin et al., 2015). High dimensional data refers to when the number of features is larger than the number of independent samples. With the increase in the number of dimensions, the number of training data needed to achieve a reasonable and small error would also increase exponentially. This issue is also referred to as Bellman's curse of dimensionality (Chang et al., 2011; Koppel et al., 2017). To overcome this, some techniques are applied to reduce the dimensions of the data points. The main goal is to ensure the significant features are restored and the learning ability of the model is not affected. Principal component analysis (PCA) is a widely used dimensionality reduction method (Richardson, 2009). But, due to the non-linear behaviour of some EOFs such as temperature, linear PCA is not always the most effective method for dimensionality reduction. Temperature effects can cause significant changes in structural parameters, which mask changes caused by damage. Non-linear fitting methods such as auto-associative neural network (AANN) was studied by Flexa et al. (2019) and Zhang et al. (2019). AANN was found to be computationally expensive as a large amount of data is needed for good performance (Malekloo et al., 2021). Flexa et al. (2019) ran some experiments based on data collected from the Z-24 bridge located between Zurich and Bern, Switzerland to compare the functionality of nonlinear principal component analysis (NLPCA) trained by AANN and PCA. The results indicated PCA had a lower percentage error (4.46%), for false damage denial compared to NLPCA's (5.24%). However, NLPCA's percentage error (2.16%) for false damage detection was considerably lower than PCA's (30.95%). Gu et al. (2017) studied an AANN-based NLPCA to train the model for damage detection in presence of high nonlinear environmental factors. The proposed model was limited to level 1 damage detection meaning it was only able to detect damage and was not able to locate the damage.

5. Feature extraction

Feature extraction is the process of identifying the damage-sensitive parameters and transforming the data to accommodate an easier damage identification for the ML algorithm. The two major techniques used for damage detection are model-driven and data-driven. To identify the damaged state, the undamaged state needs to be either developed or assumed. Furthermore, the extent of the damage can only be identified when the undamaged state is known. Many SHM cases model the structure typically using finite element (FE) modelling. The model is updated using measure values. This SHM implementation method is called model-driven. Structural complexities and the lack of data available for various joints and bonds can create model imperfections. Therefore, instead of using model-driven methods, data-driven methods use statistical pattern recognition to create a model of the structure's healthy (undamaged) state. There are four main approaches to data-driven feature extraction, as shown in Figure 3: (1) time domain, (2) frequency domain, (3) time-frequency domain, and (4) ML algorithms (Malekloo et al., 2021).

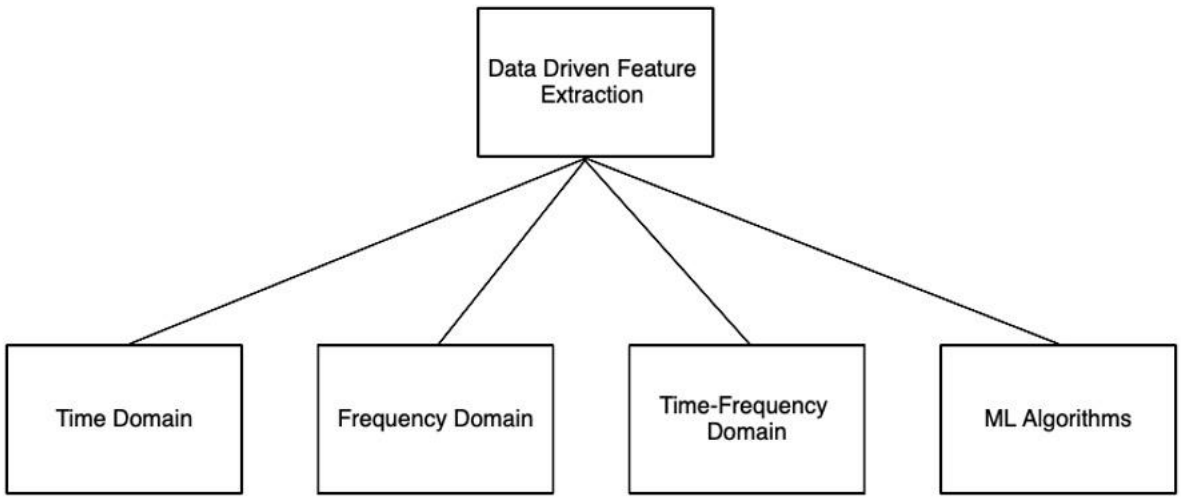

Figure 3. Main techniques in data-driven feature extraction

Time series approach is mainly used for data with low dimensions. Carden (2016) used the experimental data from the IASC-ASCE benchmark four-story frame structure, the Z24 bridge and the Malaysia-Singapore Second Link bridge; the responses created by random shocks in the time domain were fitted with autoregressive moving average (ARMA) models and the coefficients were then fed through the classifier. The ARMA model was successful at feature extraction; however, the data were recorded from forced excitation tests and this approach may not be suitable for structures where only ambient dynamic excitation is possible. Gil et al. (2015) used subspace system identification (SSI) method for a laboratory-scale composite bridge deck. The algorithm was able to successfully detect the damage to the structure; however, in a real-life scenario, this would have been difficult due to the high-dimension nature of the data gathered from a large structure.

To overcome high dimensionality frequency-domain methods can be used. Frequency response function (FRF), impulse response function (IRF) and frequency domain decomposition (FDD) are some examples used for feature extraction. The main drawback of using these methods is the inability to localise the damage and require a high quantity of data for sensitivity analysis as the reproducibility of the models in different time frames is inconsistent when factoring EOFs. (Malekloo et al., 2021).

Unsupervised ML methods have also been studied to aid feature extraction. Unsupervised feature detection consists of two main methods: (1) filter method and (2) wrapper method (Solorio-Fernández et al., 2020).

With the filter method, the most relevant parameters of the data are selected, and features are evaluated based on the intrinsic properties of the data without using any clustering algorithm. The main advantage of this method is its speed and scalability (Solorio-Fernández et al., 2020). The wrapper method, however, uses a clustering algorithm to feature subsets. The main disadvantage of this method is its expensive computational power requirement (Shokravi et al., 2020).

6. Pattern recognition

Pattern recognition (PR) is used to identify the healthy state of a structure. Within ML there are two basic approaches to train a model: supervised learning and unsupervised learning. Supervised algorithms are mainly used when the damaged state data is available. Supervised learning methods use labelled data to train the model and are used for classification and regression problems. However, unsupervised learning methods do not need labelled data to train the model and are used for clustering, association, and dimensionality reduction problems (Zhao & Liu, 2007). In the case of SHM for a bridge, supervised methods require data on the damaged state of the bridge. This may not be possible in all scenarios, sometimes it is not feasible to gather damaged data; in these cases, unsupervised learning methods are used. The algorithm is chosen based on various factors such as the number of data points or the effects of EOFs on identifying damage.

6.1 Decision tree

Decision tree (DT) is a widely used algorithm for non-parametric supervised learning. This method is capable of tackling classification problems (damaged/undamaged) and regression problems (signal comparison with the healthy state of the system (Mariniello et al., 2021). In DT algorithm, the first node is called the root node, and represents the input data. The root node splits into decision nodes. The nodes that do not split any further are called terminal nodes. The process of eliminating decision nodes to prevent overfitting is called pruning. The decision-making process is based on the threshold set by the algorithm to analyse the features. For each of the sub-nodes, information gain is calculated, information gain is the impurity of the node. This process is continued until a terminal node with the impurity of zero is calculated. The downside of this algorithm is when N multiple damage-sensitive features are available, this would make the selection of the root node difficult. A random selection of root node can lead to poor results (Gordan et al., 2021).

Mariniello et al. (2021b) used the DT method to identify and localise damage in a structure. For this approach, a calibrated FE model, or laboratory tests are needed to generate numerous damage scenarios for the structure to train the model. This model was only tested on laboratory-scaled and numerical models and has not yet been tested on a real structure.

Peng et al. (2021) studied a low-error SHM strategy by constrained observability method (COM) and DT. They used both an analytical model and a real bridge to validate the model. However, in their studies, modelling errors were not considered which can impact the results. Also, the operational loads such as the moving traffic on the bridge were not considered; these loads can change the modal parameters of the bridge and affect its behaviour.

6.2 Random Forest

Random forest (RF) is another supervised learning method which can solve regression and classification problems. This method can overcome the issues faced with DT when extensive features are present (Tufiși et al., 2021). RF is a collection of random DTs; this makes the model less sensitive to the training data. Each tree is made of a random set of the training dataset. Not all features would be used to train the trees, the features are also selected at random for each tree. Once each tree has been formed, to create a prediction, the new data points are passed through each tree. For example, in a case of a damaged/undamaged classification, if 6 trees are formed and the outcome of 4 trees predicts a damaged state, we can say the predicted outcome is ‘damaged’. In a review paper by Laory et al. (2014) different methodologies for predicting the natural frequency variation of a suspension bridge were studied and it was found that RF was a more suitable method compared to methods such as support vector regression (SVR) and artificial neural network (ANN) due to its nonlinear behaviour. It was also found that RF is computationally expensive and can take a long time to train.

6.3 Support vector machine

Support vector machine (SVM) is a supervised learning method. The data points are represented in a higher, constructed N-dimensional space and the coordinates are the features of the data point. This method classifies the points by drawing a hyperplane. The aim is to find the best hyperplane to separate the categories, in this case, damaged and undamaged. The distance between the hyperplane and the point of each category is called the margin, the maximum margin on both sides of the hyperplane leads to better classification and points that fall exactly on the margin are called the supporting vectors (Zhou et al., 2021). Figure 4 demonstrates the hyperplane drawn with the attempt of having a maximum margin on both sides of the hyperplane.

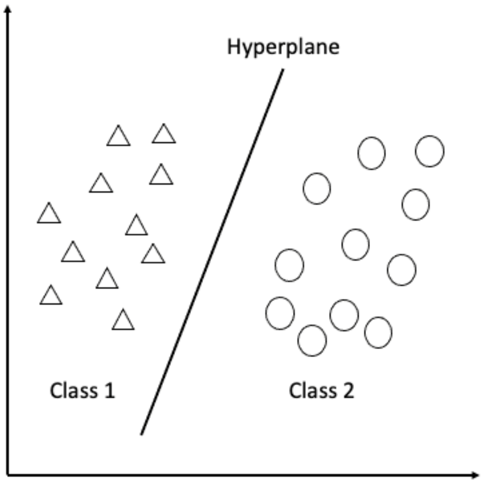

Figure 4. Classification using support vector machine

When the data is non-linearly separable, or non-linearity is expected, the SVM relies on the Kernel trick. A kernel function maps the data into a higher dimensional features space, where drawing a hyperplane between classes becomes possible. When kernels are appropriately chosen, the mapping is computationally stable and inexpensive (Trick, 2014). Figure 5 illustrates the Kernel trick applied when the data is non-linearly separable.

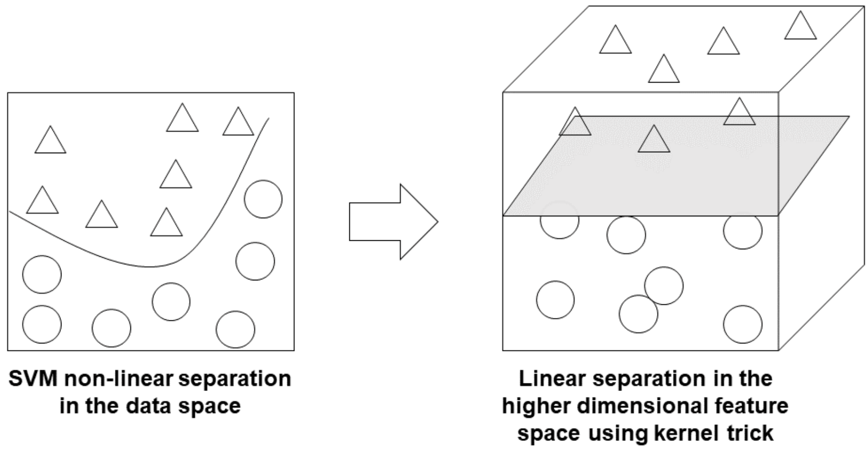

Figure 5- Kernel trick illustrated

In SHM applications usually, the number of data points and dimensions is high and in a recent study carried out by Gordan et al. (2021) SVM was able to outperform the classification and regression tree (CART) method. Although an increase in the number of training data for the SVM method leads to a more accurate model, it increases the training time exponentially (Laory et al., 2014). Satpal et al. (2016) applied SVM for damage identification and localisation in aluminium beams. They used both simulated and experimental data to test the model. The model showed promising results with the simulated data but when noise was applied to the experimental set-up the prediction capability of SVM deteriorated showing that SVM is sensitive to noise present in the data.

6.4 K-nearest neighbour

K-nearest neighbour (KNN) is a traditional supervised machine learning algorithm which can solve both regression and classification problems. It classifies the input data based on their distance to the test dataset. Figure 6 shows how KNN classifies the new data point based on the distance between the new data point and the available classes.

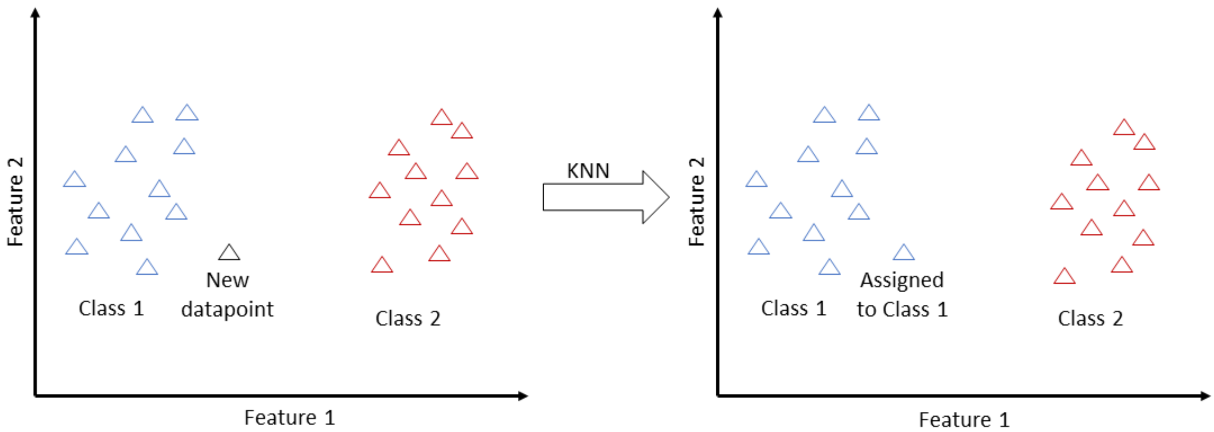

Figure 6. Clustering-based classification using k-nearest neighbour

The selection of how many neighbours to consider is a function of noise in the data. In SHM the features have high dimensionality which makes KNN computationally expensive since a large dataset is needed to train the model (Malekloo et al., 2021). Li et al. (2020) compared deep learning algorithm against KNN, SVM and DT to identify damage to a cable-stayed bridge. The data was gathered via a 1:40 scaled-down model where the deflection of the bridge was recorded at a sampling rate of 150 Hz. All machine learning methods were conducted under ten-fold cross-validation. The results show the average accuracy of automated detection of CNN model (96.9%) was better than RF (81.6%), SVM (79.77%) and KNN (77.7%). Figure 7 shows that KNN had the largest accuracy distribution between the four methods. This phenomenon may be related to the relatively lower algorithm complexity of KNN (Li et al., 2020; Thanh Noi & Kappas, 2017).

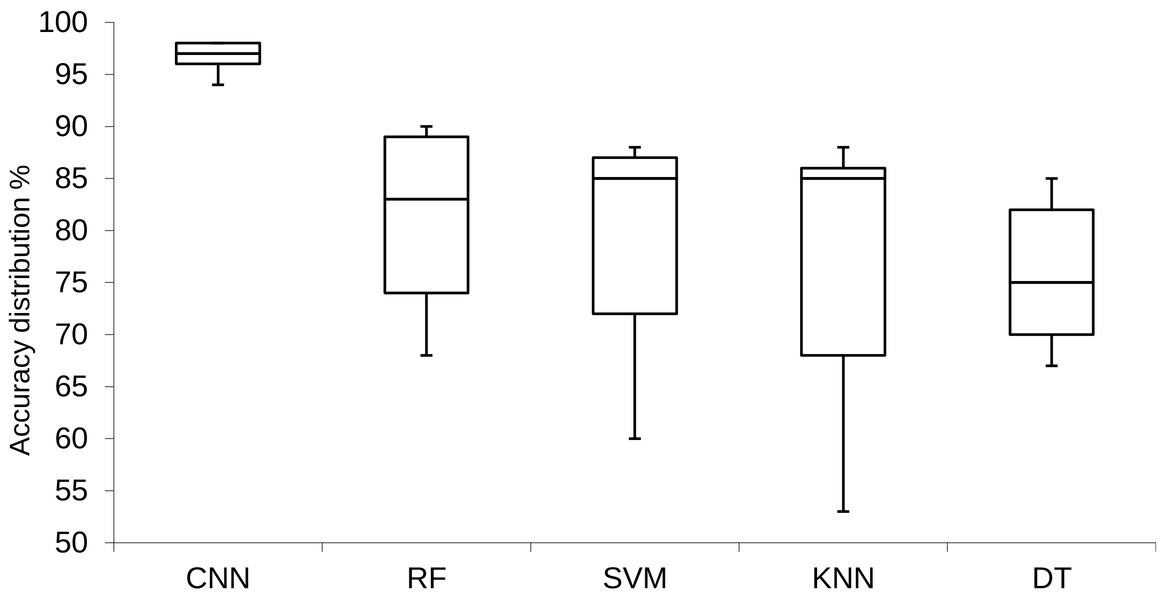

Figure 7. Accuracy distribution based on the detection method (Li et al., 2020)

Feng et al. (2021), proposed a KNN algorithm for locating and quantifying stiffness loss in a bridge from forced vibration due to a truck crossing at low speed. The KNN algorithm was used to search for the patterns of forced eigenfrequencies that are closest to the on-site instantaneous frequencies to determine the location and severity of the damage. Results have shown that damage can be detected, and in optimal cases, located and quantified, with some noticeable unfavourable locations near the supports. However, overall accuracy has been compromised with an increase in speed and road roughness, which broadens the discrepancies between eigenvalue analysis and dynamic transient analysis.

6.5 Bayesian

Naïve bayes (NB) is a method based on Bayes' theorem, it is assumed that no dependencies between the features. Mangalathu et al., (2020) studied eight ML methods including NB, KNN, DT and RF to identify the seismic failure mode of reinforced concrete (RC) shear walls. NB was ranked the sixth most accurate learning method in this study. The authors concluded the inaccuracy of the NB method was due to the existence of a nonlinear decision boundary between the failure methods.

Nazarian et al. (2018) studied post-event assessment of damage in a turn-of-the-century six-story building with timber frames and masonry walls. The building was damaged due to the differential settlement of its foundation. The authors used FEM to generate stiffness and strain datasets. Sensor noise was also considered in training the model by simulation 1000 different versions of white noise of up to 10% of the extracted strains. They used neural network (NN), SVM and gaussian naïve bayes (GNB) to train the SHM model. Table 1 showcases the prediction accuracy of the three ML methods. Table 1 indicates NN was the most accurate and when the noise level reaches 10% the accuracy of all three methods dropped significantly; therefore, a noise level of up to 8% was used to train the model.

Table 1-. Prediction accuracy (Nazarian et al., 2018)

Noise level (%)	SVM prediction accuracy (%)	NN prediction accuracy (%)	GNB prediction accuracy (%)
2	97	98	98
4	96	96	96
6	91	93	92
8	86	90	88
10	79	86	83

6.6 Artificial neural network

Artificial neural network (ANN) is a learning algorithm which loosely models the way nerve cells work in the human brain. This method consists of at least three layers, (1) input layer, (2) hidden layer(s), and (3) output layer.

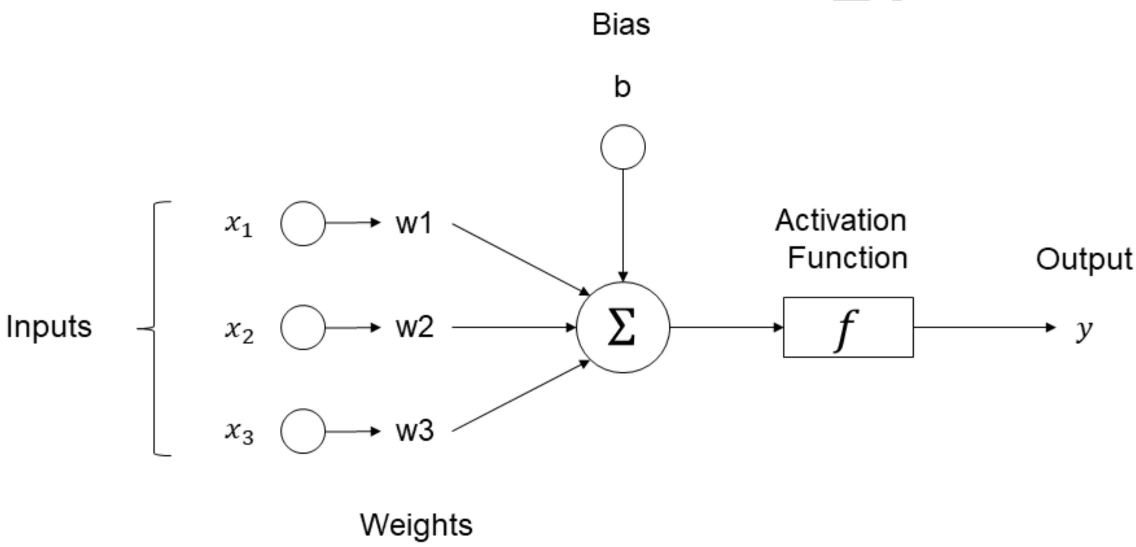

Figure 8- Schematic representation of a neuron in a neural network

Each layer is made of a series of neurons which have several connections to the previous and next layer. Each connection has a 'weight' associated with it. Weight is a trainable factor of how much of the input to use. Weights get multiplied by the input, then all the input x weights values flow in one neuron. The values are then summed and a 'bias' is then added. Bias is another trainable parameter and is set to offset the output either positively or negatively (Kwon, 2011). Each node's output is decided by its non-linear activation function.

Figure 8 shows a schematic representation of a neuron and how the output of a neuron is decided. An activation function transforms the summed weighted input from the node into an output value fed to the next layer. As the training data set is fed through the model, the output is measured against the labelled data via an error propagation algorithm(Jiang et al., 2014). Figure 9 showcases a simple ANN model and how the layers are interconnected. With repetition, the value of the weights and biases of the model alter to create a model capable of correctly predicting the outcome of the input. This method requires a labelled training dataset meaning this is a supervised ML method. Malekjafarian et al. (2019) used a two-stage machine learning approach for bridge damage detection using the responses measured on a passing vehicle. In the first stage, the ANN is trained using the vehicle responses measured from multiple passes over a healthy bridge. Root-mean-square was used to calculate the error between the predicted and the measured responses between each passage. The second stage consists of a Gaussian process to detect the changes in the disruption of the predicted errors. This is how the damage was detected.

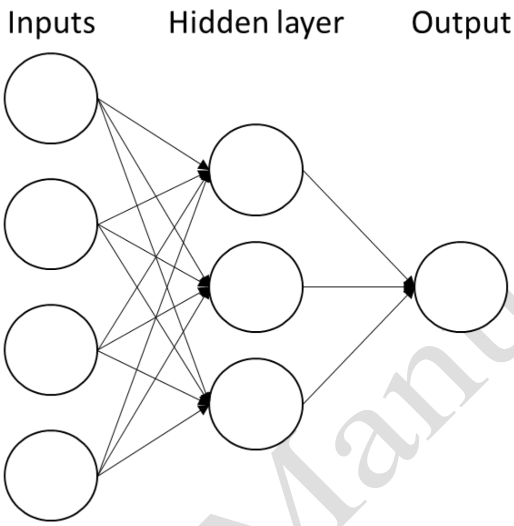

Figure 9- Basic ANN model and how the layers are connected

6.7 Self-organising map

Self-organising map (SOM) is an unsupervised learning approach. It uses for clustering, mapping, and dimensionality reduction techniques to map multidimensional data onto lower-dimensional whilst preserving the topological structure of the data. SOM uses competitive learning instead of error-correction learning. SOM training is based on internal properties between inputs and does not require input-output samples (Tibaduiza et al., 2011). Avci et al. (2019), studied SHM with SOMs and ANNs. This technique used is also called autoencoder. Autoencoders have an hourglass-like structure and are made of three parts, encoder, code, and decoder. The encoder compresses the input data into an encoded representation which is several orders of magnitude smaller than the input data. Code contains the compressed knowledge. The decoder decompresses the data and reconstructs the data back from its encoded form. A loss function is then introduced to compare the reconstructed and actual data. This method can be used to create a reduced order model and allow focus only on areas of interest (Feijóo et al., 2021). Figure 10 shows how SOM (encoder) was used to compress the input data and then with the aid of ANN (decoder), the input data is reconstructed. The analytical data used for the study was based on a structure made up of six columns and two girders and seven cross beams. For the simulation, 21 accelerometers were assumed. The vibrations environment for the ambient condition was modelled as a stationary white noise signal in the gravity direction. The damage scenarios were simulated with a modification of the beams' stiffness and changes in boundary conditions. They used

SOMs to process the ambient condition acceleration data in the time domain for a topology map for each joint, this creates topology maps for the undamaged state. For damage assessment, the measured topology maps are compared against the healthy state topology maps to determine the state of the structure.

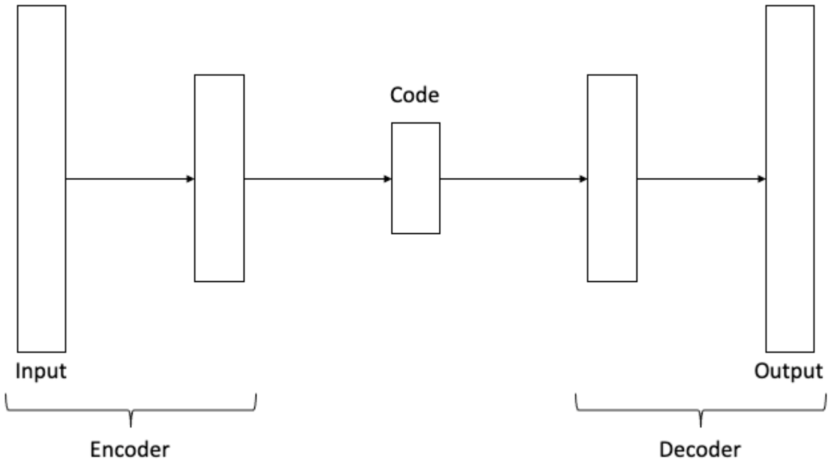

Figure 10. The autoencoder method used to regenerate the input from the encoding

Several studies concluded that SOM has superiority over PCA in dimensionality reduction analysis. Reusch et al., (2007) have experienced overlapping of patterns using PCA due to its orthogonal constraint where SOM was more efficient in extracting patterns. SOM provides better results compared to PCA when the data is more complex and has nonlinear characteristics (Laitinen et al. 2002; Aguado et al. 2008).

6.8 Gaussian mixture model

Gaussian mixture model (GMM) assumes there are certain numbers of Gaussian distributions, where each distribution represents a cluster. This unsupervised learning method is capable of both hard and soft clustering (Y. Zhang et al., 2021). Figueiredo and Cross (2013) compared GMM with nonlinear principal component analysis (NLPCA), factor analysis, the mahalanobis squared distance (MSD), and principal component analysis (PCA) for bridge monitoring. This study was performed on data sets from the z-24 Bridge, Switzerland. Nonlinearity was present in the data set at times of freezing temperatures. It was found the GMM-based algorithm had the best classification performance in terms of the reduced number of false alarms. The study also showed PCA, and MSD-based algorithms are not suitable for long-term monitoring because are unable to remove nonlinear patterns from the baseline condition data during the training process which leads to a high number of false alarms.

7. Conclusion

To conclude this review, Table 2 shows some of the ML methods used in recent years in different areas of SHM. As can be seen, most of the studies were based on supervised learning methods. Supervised learning methods need to have data for the damaged state of the structure which is a drawback. Therefore, exploring unsupervised methods can be beneficial for the SHM field as it is not feasible for most structures to be damaged for data collection purposes. Choosing the right method of ML mainly depends on the dimension, linearity, and availability of data, therefore before choosing a particular method these parameters should be considered. ML has the potential to uncover the influence of EOFs due to their multivariate encapsulation capabilities. Despite all the research done in this field, there is an apparent gap in unsupervised SHM frameworks. Unseen conditions of real damage obstruct training possibilities, which can be barely fulfilled by synthetic datasets or physical-based realizations. Nevertheless, further advancements with label-free approaches such as population-based SHM can find remedies to the ongoing learning problem in SHM systems. It is obsolete that a fully automated SHM relies on this direction yet has a long way to propose its globally accepted frameworks.

Table 2- Machine learning methods used in different areas of structural health monitoring

Area in SHM	ML method	Supervised/ Unsupervised	Aim	Results
Data acquisition	Hybrid of Genetic Algorithm (GA) and Artificial Neural Network (Banik & Das, 2020)	Supervised	To use Neuro- Genetic Algorithm in sensor optimisation for SHM.	Neuro-GA hybrid showed better convergence and a minimal number of generations compared to regular GA.
Data imputation	Bayesian temporal factorisation (X. Chen & Sun, 2021 ; Z. Chen et al., 2019 ; Ren et al., 2020)	Supervised	Using Bayesian temporal factorisation to achieve efficient imputation and prediction of structural response in long-term SHM.	This method was successfully tested to impute strain and temperature records of a concrete bridge.
	Generative adversarial networks (GAN) (Siahkoohi et al., 2018)	Supervised	To reconstruct heavily sub-sampled seismic data using GAN	This model assumed that 5% of the gathered data is fully sampled. And with that, it was able to reconstruct all the other slices with 90% randomly or column-wise missing entries.
Data Compression	Auto-associative neural network (AANN), (Flexa et al., 2019 ; Gu et al., 2017 ; H. Zhang et al., 2019)	Unsupervised	Data normalisation in SHM by using AANN	The proposed model had a percentage error of 4.46% for false denial of damage and 2.16% for false indication of damage.

Feature extraction	Autoregressive Moving Average (ARMA) (Carden, 2016)	Supervised	ARMA was used to extract features of the Z24 bridge, the IASC-ASCE benchmark four-story frame structure and the Malaysia-Singapore Second Link bridge.	The model was successful at feature extraction, but the downside of this method is the data from the bridges and the structure were from forced excitation and this approach may not be possible for other structures.
	Subspace System Identification (SSI) (Gil et al., 2015)	Supervised	To use SSI to detect damage from a laboratory-scale composite bridge	The proposed model but successful, however, in a real-life scenario this method will not be feasible due to the high dimensionality of the data.
Pattern recognition	Decision tree (DT)(Gordan et al., 2021 ; Mariniello et al., 2021a)	Supervised	Damage detection and localisation using DT and vibration data	The model attained 91%,87% and 84% mean accuracy for 3%,6% and 9% noise and with an average localising error of 1.48 m. This method relies on an accurate FE model of the structure.
	Support vector machine (SVM) (Gordan et al., 2021; Laory et al., 2014; Zhou et al., 2021)	Supervised	Structural damage identification of composite bridge using SVM	The SVM models were conducted using various kernel functions consisting of linear, sigmoid, polynomial, and radial basis function (RBF). And SVM-polynomial was the most accurate model.
	K-Nearest Neighbour (KNN)(Li et al., 2020; Thanh Noi & Kappas, 2017)	Supervised	Comparison of KNN, SVM, CNN and DT to detect damage for a cable-stayed bridge	KNN had the largest accuracy distribution between the four methods. This could be due to its relatively lower algorithm complexity.

	Bayesian (Mangalathu et al., 2020; Nazarian et al., 2018)	Supervised	SHM model trained using NN, SVM and gaussian naïve bayes (GNB) with data gathered from a small-scale cable bridge	NN had the highest accuracy of the three with an accuracy of 86% when the noise level reaches 10%. GNB's accuracy was 83% for the same noise level.
	Artificial neural network (ANN) (Malekjafarian et al., 2019; Malekloo et al., 2021)	Supervised	Bridge damage detection using responses measured on a passing vehicle	The data gathered was through a FE model. The proposed method was able to identify damage; however, for real-world applications, a damage indicator must be introduced to the system due to other environmental factors which could also change the behaviour of the bridge.
	Self-organising map (SOM) (Avci et al., 2020; Tibaduiza et al., 2012)	Unsupervised	Damage detection based on the ambient response of a structure using SOM and ANN	Nonparametric damage detection algorithm with trained SOMs was successful at quantifying structural damage; however, the distribution of the index values throughout the laboratory structure indicates that the algorithm was not able to localise the damage. Therefore, a pattern recognition neural network is trained to identify the pattern of the damage index magnitudes. The ANN improvement allowed the algorithm to be able to locate damage as well as identify it.

Table 3- List of used abbreviations

Abbreviation	Definition	Abbreviation	Definition
AI	*Artificial intelligence*	**KNN**	*K-nearest neighbour*
ANN	*Artificial neural network*	**ML**	*Machine learning*
AANN	*Auto-associative neural network*	**MSD**	*Mahalanobis squared distance*
ARMA	*Autoregressive moving average*	**NB**	*Naïve bayes*
BTF	*Bayesian temporal factorization*	**NN**	*Neural network*
CART	*Classification and regression tree*	**NLPCA**	*Nonlinear principal component analysis*
COM	*Constrained observability method*	**OSP**	*Optimal sensor placement*
DT	*Decision tree*	**PR**	*Pattern recognition*
EOF	*Environmental and operational factors*	**PCA**	*Principal component analysis*
FE	*Finite element*	**RF**	*Random forest*
FDD	*Frequency domain decomposition*	**RC**	*Reinforced concrete*
FRF	*Frequency response function*	**SOM**	*Self-organising map*
GMM	*Gaussian mixture model*	**SHM**	*Structural health monitoring*

GNB	*Gaussian naïve bayes*	***SSI***	*Subspace System Identification*
GAN	*Generative adversarial networks*	***SVM***	*Support vector machine*
GA	*Genetic algorithm*	***SVR***	*Support vector regression*
IRF	*Impulse response function*		

7. References

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