Feature Extraction Methods for Neural Networks in the Classification of Structural Health Anomalies

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Abstract: Failure of large complex structures such as buildings and bridges can have monumental repercussions such as human mortality, environmental destruction and economic consequences. It is therefore paramount that detection of structural damage or anomalies are identified and managed early. This highlights the need to develop automated Structural Health Monitoring (SHM) systems that can continuously allow the safety status of structures to be determined, even in the worst and most isolated conditions, to ultimately help prevent destruction and save lives. Signal processing is a crucial step to detecting structural anomalies and recent work demonstrates the opportunities for neural networks, however the encoding of data for SHM requires the extraction of features due to often, noisy data. This paper focuses on feature extraction methods for artificial neural networks (ANNs) and spiking neural networks (SNNs) and aims to identify bespoke features which enable SNNs to encode data and perform the classification of anomalies. Results show that extraction of particular features in large real-world applications improve the classification accuracy of SNNs.

1 INTRODUCTION

Large man-made civil infrastructures exercise an important role in both the societal and economical evolution of the modern world (Khemapech, Sansrimahachai & Toahchoodee, 2016; Song et al, 2020). Structures such as bridges, tunnels and buildings are used on a daily basis by billions of people worldwide, to complete day-to-day activities (Khemapech, Sansrimahachai & Toahchoodee, 2016). With this in mind it is critical that complex structures such as these, are continually fit for their intended purpose and are safe for human use (Ibrahim et al, 2020). This is a challenging task as throughout their operational lifetime, artificial structures are highly vulnerable to damage (Li et al, 2015). Exposure to a number of environmental, anthropogenic and operational factors can all contribute to causing structural deterioration (Abdeljaber et al, 2017). There are many different types of damage that can surface, for example in the forms of corrosion, erosion, degradation or decay, all of which have the potential to cause structural collapse and require continuous monitoring (Abdeljaber et al, 2017). Areas that are incredibly difficult to access or that are susceptive to natural disasters like landslides, earthquakes or forest fires are often affected by such catastrophic devastation (Moaveni et al, 2011). Disasters such as these can occur without warning so preparation is crucial, having functional and well-maintained infrastructure is extremely important, as it will reduce the potential aftermath of future disasters (Pang et al, 2020).

Traditionally, the severity of damage to a structure is visually assessed by experienced human inspectors, who physically examine any structurally unsound sites (Pang et al, 2020). Visual analysis, despite the extensive efforts of inspectors, experience a number of challenges; restricted access to damaged locations, lengthy inspection completion times and regular

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manual structural maintenance assessments (Hernandez, Roohi, & Rosowsky, 2018).

Additionally, localized experimental fault detection techniques such as radiographs, thermal field methods and acoustic or ultrasonic approaches have also, been used to identify structural damage (Doebling et al, 1996). However, the issue with these methods is that the damaged areas must be known and accessible for inspection prior to experimental analysis (Doebling et al, 1996). These limitations highlight the need to computerise this monitoring process to make identifying, locating and determining damage more efficient and accurate (Song et al, 2020).

This has led to the need to develop automated SHM and damage identification systems that can detect and monitor infrastructural damage, without human interaction (Anton, Inman & Park, 2009; Moaveni et al, 2010). These physical SHM systems need to be accurate and efficient whilst remaining operational for extended periods, for example, in buildings, and concealed in concrete infrastructures (Abdo, 2014; Yu, Wang, & Meng, 2005). A key challenge that needs to be considered is how to effectively manage and process large amounts of raw data obtained from these systems whilst still being able to classify structural damage correctly and efficiently. This, therefore, establishes the focus for this paper; to investigate the extraction of specific features from large real-world datasets, in order to achieve the highest degree of accuracy possible when applied to brain-inspired solutions.

The remainder of this paper is organised with section 2 outlining an overview of SHM, neural networks and the key challenges. Section 3 defines the selected SHM dataset/application and the analysis of various feature extraction techniques. Section 4 reports on the accuracy evaluation of both ANN and SNN networks based on bespoke extracted features. Finally, section 5 discusses future work and provides a conclusion.

2 BACKGROUND

It is inevitable that structures will degrade over time due to a number of factors, including frequent use and environmental causes like soil erosion, flooding or unexpected anomalies like earthquakes, landslides or forest fires (De La Torre et al, 2020). It is therefore paramount, for both safety and financial reasons to monitor large complex infrastructures such as buildings, bridges, dams and railroads, on a regular basis (Nuhu et al, 2020). SHM is an engineering field that focuses on developing damage identification systems that can monitor and evaluate the condition and stability of man-made structures (Crémona, 2016; Semperlotti, 2009). The techniques used are designed to enable early damage detection, allowing preventive measures to be implemented to avoid structural failure, such as required maintenance and structural reinforcement (Couture, 2013).

SHM has progressed rapidly in recent years, due to the evolution of sensor networks, data processing and information management (Li et al, 2015). This automation has led to the development of increased precision and financially feasible data acquisition systems, as well as rapid growth in dataset size (Crémona, 2016). There are, however, still challenges that need to be addressed.

2.1 Structural Health Monitoring (SHM) Techniques

To achieve a high level of accuracy and reliability, SHM systems need to have a well-designed damage classification framework, that enables structural damage to be detected (Ying et al, 2013). Figure 1 shows the process of damage identification is comprised of four core stages. The stages include: 1) signal monitoring, 2) signal processing, 3) feature extraction and 4) classification (Amezquita-Sanchez & Adeli, 2015; Goyal & Pabla, 2015).

Data is obtained from a sensor network and digitised during the signal monitoring stage. Signal processing methods such as Fourier transforms, Hilbert-Huang transforms, statistical time series models, Wavelet transforms and Cohen's class are then used, to examine the data in order to extract, determine and categorise core features (Goyal & Pabla, 2015). Feature extraction, for example the orthogonal decomposition technique, is then carried out using measured data, to detect anomalous information with the goal of revealing non-obvious damage states (Eftekhar Azam, Rageh & Linzell, 2018; Overbey, 2008). Feature extraction, is therefore, a key step in the damage identification process. A number of techniques have been used previously during the classification stage to identify structural damage accurately and correctly. These methods include clustering algorithms, specifically K-means (KM) clustering, Support Vector Machines (SVM), Artificial Neural Networks (ANN), Spiking Neural Networks (SNN) and Hybrid Classifiers (Goyal & Pabla, 2015).

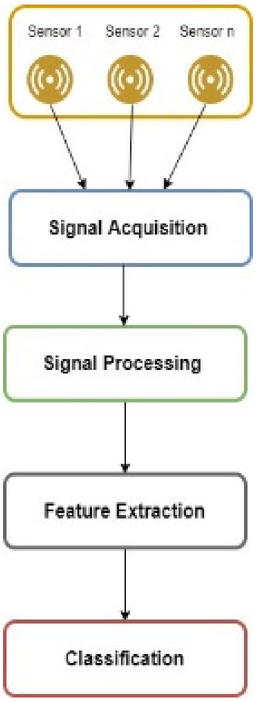

Figure 1: Four main damage identification stages within a SHM system.

2.2 Artificial and Spiking Neural Networks

ANNs consist of a number of vastly connected processing nodes (neurons) that operate concurrently (Keller, Liu & Fogel, 2016). These networks learn as a result of training which is performed using datasets where the input and output data is known (Keller, Liu & Fogel, 2016). This data is used to train the neural network and modulate the synaptic weights between neurons (Keller, Liu & Fogel, 2016). ANNs are a very beneficial tool as they have the functionality to extract trends from input data (Notley & Magdon-Ismail, 2018). However, despite this, factors such as power utilisation and the expense of implementing them in hardware as edge computing devices, presently do not meet practicality requirements for anomaly detection in real world, always-on applications (Pang et al, 2020).

The original concept of ANNs has progressed rapidly to develop generations of ANNs, which mimic more closely the biological principles for learning and fault tolerance (Pang et al, 2020). SNNs are considered to be the third generation of ANNs (Paugam-Moisy & Bohte, 2012). Derived from neuroscience advancements and brain inspired natural computing, these networks use an adapted version of the spike timing of neurons to encode and process information (Liu et al, 2017). Similar to biological NN, SNNs enable communication through incorporating electrical pulses (spikes) (Zhang, Gu, & Pan, 2018) with the concept of time illustrated in Figure 2 In SNNs, information is communicated via the timing between spike events or frequencies. The integration of multiple frequencies enables a spiking neuron to aggregate the frequencies to reflect a membrane voltage increase within the neuron. When a threshold is exceeded, the neuron produces a single spike output. This process enables temporal patterns to be identified via training of synaptic weights which impact on the contribution to the neuron's membrane voltage.

There are a number of models that have been developed to determine the impact of action potential spikes on selected neurons, these include the Hodgkin-Huxley (HH) model, the leaky integrate-and-fire (LIF) model and the adaptive exponential integrate-and-fire (AdExIF) model (Paugam-Moisy & Bohte, 2012). The LIF model is the least computationally expensive, in comparison to the HH model which is deemed the most expensive (Paugam-Moisy & Bohte, 2012).

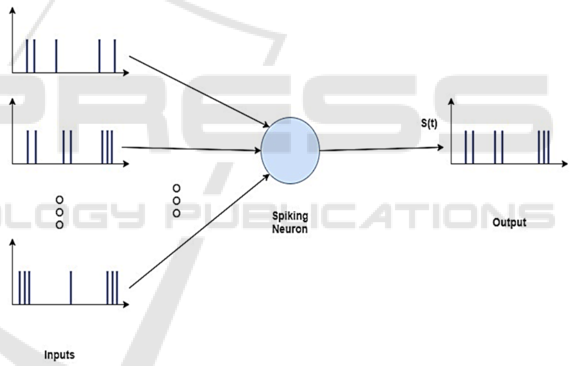

Figure 2: Communicating information in SNNs.

Research to date has established the ultra-low power capability of SNNs in hardware due to the fact that energy is only consumed when an input spike is received and processed, resulting in an overall saving of power (Zhang, Gu, & Pan, 2018). Currently SNNs have shown benefit in SHM system development, as compared to ANNs, as the hardware expense is more cost-effective and power efficiency is improved (Pang et al, 2020).

The key challenge is the extraction of features from the SHM data and the encoding of identified features which improve the accuracy of the network. This is challenging as the data from sensors (e.g. accelerometers) is highly variable.

3 DATASET & FEATURE ANALYSIS

The identification of suitable benchmark data was a key step, and the Qatar University Grandstand Simulator (QUGS) (Avci, 2018) was selected due to the availability of a full range of structural failures across a known structure with labelled data points. This dataset has also been used in several other works (Abdeljaber et al, 2016; Abdeljaber et al, 2017; Avci et al, 2018; Kiranyaz et al, 2021) and will form the basis for benchmarking of performance.

The data was originally used by Abdeljaber et al. (Abdeljaber et al, 2017) to develop a 1D convolutional neural network (CNN) for vibration based SHM, with the primary intention of developing damage identification approaches that can efficiently monitor present-day infrastructure (Kiranyaz et al, 2021). The simulator is situated in a laboratory environment and is reported as the biggest stadium framework constructed in a controlled environment (Abdeljaber et al, 2016), shown in Figure 3.

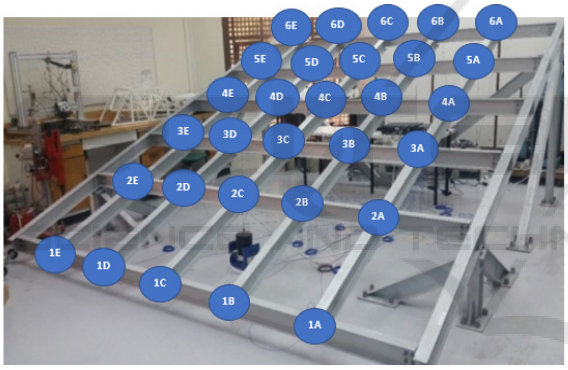

Figure 3: QUGS Sensor Point Locations Identified. Source: Adapted from (Abdeljaber et al, 2017).

Devised to hold 30 observers, the main hot-rolled steel shell is 4.2m x 4.2m in size (Abdeljaber et al, 2017). The QUGS has a total of 30 structural joints (shown as 1A to 6E in Figure 3), in which 30 accelerometers are used to measure the structural vibrational response (Kiranyaz et al, 2021). The steel frame is equipped with 27 PCB model 393B04 accelerometers and 3 B&K model 8344 accelerometers (Abdeljaber et al, 2017). Vibration was applied to the structure through the use of a modal shaker, that used a SmartAmp power amplifier, to implement the signal to the shaker (Abdeljaber et al, 2017). Finally, the production of the shaker input and recording of the acceleration output are achieved through using two 16-channel data acquisition instruments (Abdeljaber et al, 2017).

Structural damage is injected by slackening the bolts at a specific joint, which is a very slight alteration to the structure's rotational stiffness (Kiranyaz et al, 2021), as displayed in Figure 4.

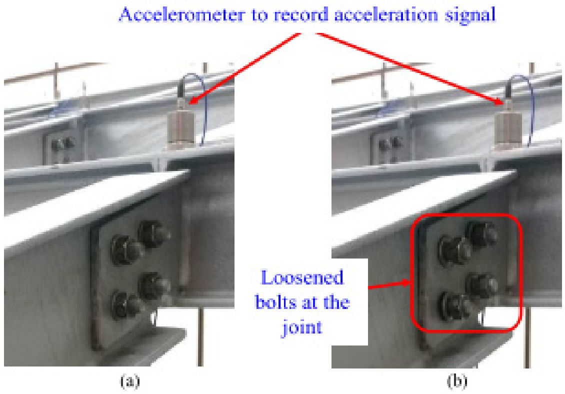

Figure 4: Demonstration of How Structural Damage is Artificially Applied in the QUGS. Source: Adapted from (Kiranyaz et al, 2021).

There were 31 damage tests implemented; 1 undamaged (healthy) case for benchmarking purposes and 30 damaged cases to simulate structural anomalies (Avci et al, 2018). Each scenario was recorded for 256 seconds, at a sampling frequency of 1,024Hz, resulting in a total of 262,144 samples per joint per test (Avci et al, 2018). This, therefore, results in a total of 243,793,920 samples for the entire dataset.

The particular reasons outlined demonstrate that the QUGS dataset provides an ideal range of anomalies for data training and evaluation purposes of the neural networks.

3.1 Raw Data

The QUGS dataset has a significantly large number of raw data samples, 243,793,920 in total. This data when graphically displayed is extremely noisy and difficult to discern any visual trend or features, due to high frequency sampling. It is therefore very difficult to distinguish whether a sample is of a damaged or undamaged state as seen in Figure 5.

Using this data in its raw form will make it tremendously challenging for any classification technique to determine the structural state accurately. Therefore, feature extraction was required to ensure that any potentially masked damage states reported in the sensor data are identified and to consolidate to key element of interest (Amezquita-Sanchez & Adeli, 2015).

Hence, feature extraction is a critical step in the damage identification process.

3.2 Feature Selection

It is important to select features that best represent the data. Certain features may suit specific real-world datasets better than others. The choice of damage-sensitive parameters for the QUGS dataset is based on multiple different factors such as the data type and which features will best identify the health status best. There may be several features that could determine structural health accurately whilst avoiding the effect of various environmental and structural conditions (Pang et al, 2020).

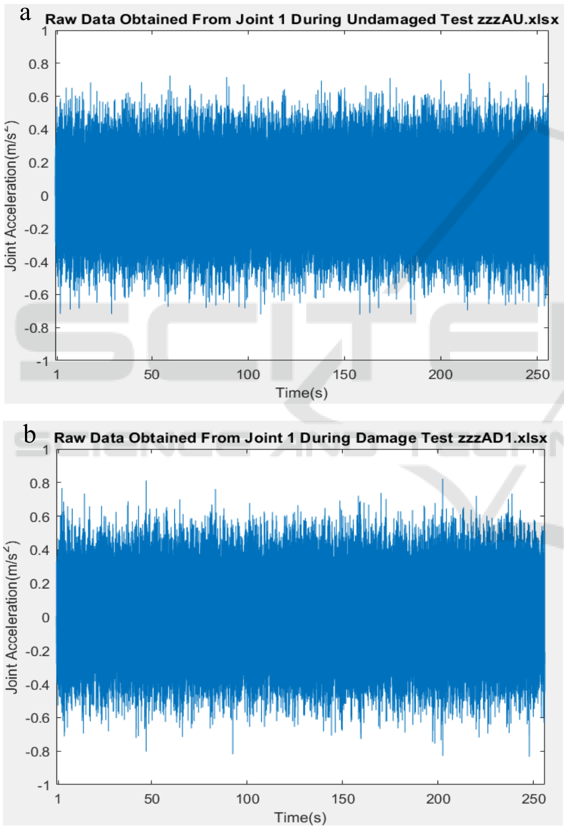

Figure 5: Displays the comparison of the raw noisy data at joint 1 between a) an undamaged sample and b) a damaged sample.

There two different types of sensors used in the data acquisition process that measure bolt vibration over a period of 256 seconds. This means that time and frequency domains, due to the nature of the data, can be used to extract specific features. These features include mean, standard deviation, variance, energy, Zero-crossing rate, and Fourier Transforms (Toivola & Hollmén, 2009). Some features proved better than others for example, zero-crossing rate only showed very minor differences between the damaged and undamaged data, when extracted from the noisy raw data, as displayed in Figure 6 and therefore was not the best feature choice.

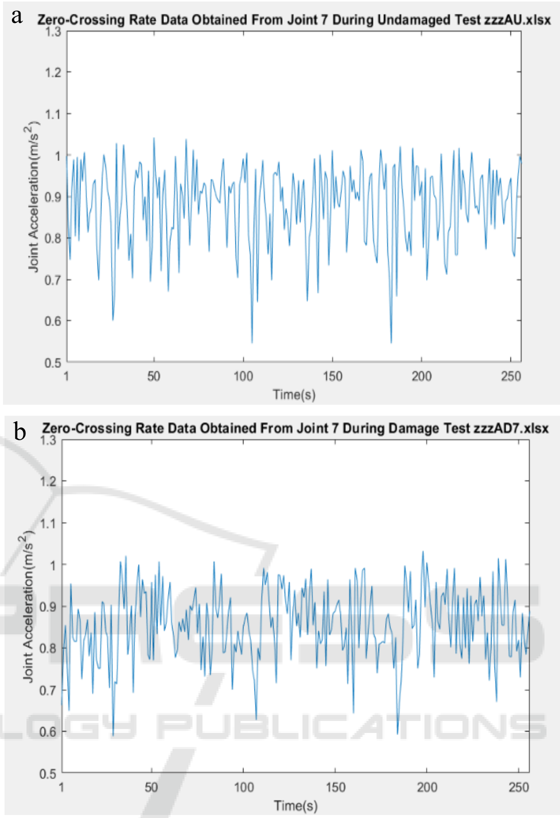

Figure 6: Displays the comparison of zero-crossing rate at joint 7 between a) an undamaged sample and b) a damaged sample.

A number of MATLAB scripts were created to firstly, extract a selection of features. These features were then displayed graphically and analysed to determine if there were any significant differences in the damaged and undamaged data. This was to ultimately determine which feature was the best choice, in aiding damage identification. After this extensive analysis process, several features: absolute mean, variance, standard deviation and Fast Fourier Transforms (FFT) were chosen, as they showed distinguished profiles between undamaged and damage data.

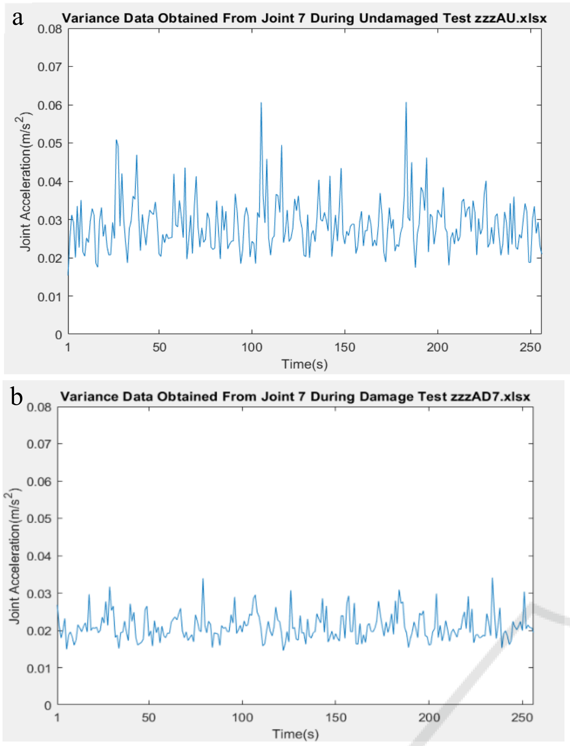

Figure 7: Illustrates the comparison of variance at joint 7 between a) an undamaged sample and b) a damaged sample.

3.3 Fast-Fourier Transform (FFT)

The Fast Fourier Transforms (FFT) proved to be the superior feature for this particular dataset, as it showed a considerable difference between the damaged and undamaged data samples, as illustrated in Figure 8.

This was identified through developing a MATLAB script that was able to graphically display a double-sided magnitude spectrum for each sample and determine the top three highest magnitudes of each one. Interestingly the frequency associated with the third highest magnitude in each comparative graph showed the largest difference in frequency between the damaged and undamaged data.

This analysis also uncovered that the frequency associated with third largest magnitude in the undamaged joints, surrounding a damaged joint, showed significant variation. In addition, looking at these as a collective instead of individually could also, prove as another technique to aid data classification, as illustrated in Table 1.

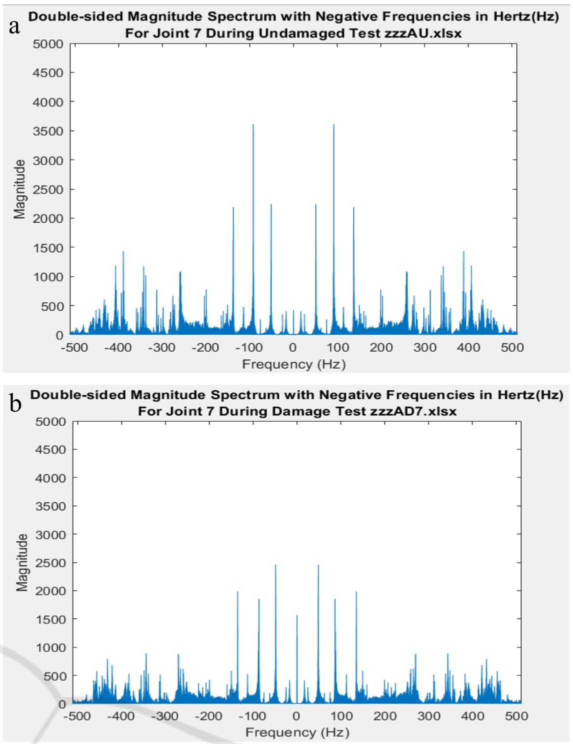

Figure 8: Displays the comparison between Fast-Fourier Transforms at joint 7 for a) an undamaged sample and b) a damaged sample.

Table 1: Displays the frequencies associated with the three largest magnitudes for joints 1B, 2A, 2B, 2C and 3B, for both the benchmark data (2B-B) and the damaged data (2B-D) when only the single joint 2B is damaged.

Frequencies (Hz) Associated with the Top Three Magnitudes	Joint Position									
	1B		2A		2B		2C		3B	
	2B-B	2B-D	2B-B	2B-D	2B-B	2B-D	2B-B	2B-D	2B-B	2B-D
1	92.07	48.99	92.07	141.4	92.07	48.69	92.07	48.69	137.60	135.4
2	51.23	48.69	137.60	48.69	91.96	48.60	91.96	48.60	137.50	135.2
3	393.80	48.60	141.80	199.9	92.25	48.99	92.25	135.4	138.20	135.3

4 NEURAL NETWORK APPLICATION

ANNs are a well-established technique making an excellent benchmark for all other future designed networks. This research aims to validate that an SNN can make a relatively accurate prediction on real world data. However, the dataset is extremely noisy due a to high frequency sampling rate, making it very challenging to classify. Therefore, it requires pre-processing in extracting and analysing several features; this establishes the contribution from the research.

Each stage of this research is depicted in Figure 9, where the main stages are: 1) Raw data obtained from the 30 accelerometers, 2) Extraction of features from the raw data, 3) Feature extracted data is inputted into neural networks and 4) Output from neural networks is determined.

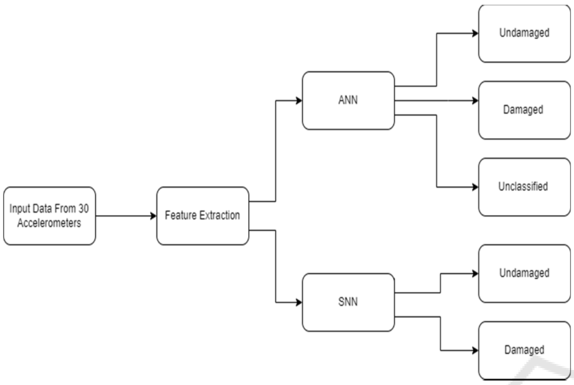

Figure 9: Illustrates a summary of the workflow for this research.

4.1 ANN

An ANN was established, using the feature extracted data as the input data. This was created to classify when an anomaly has occurred, i.e. detect if the input data reflects a healthy or unhealthy structural state. The Neural Network Toolbox in MATLAB was used to develop the ANN. The network had 30 neurons in the input layer and three output states: the three outputs were predetermined prior to classification; *undamaged*, *damaged* or *unclassified*.

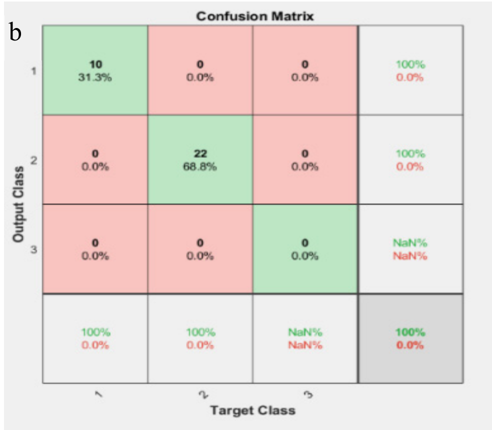

Figure 10: Presents the confusion matrixes for the ANN for a) training and b) testing.

The network was trained using 75 percent of the feature extracted samples and tested on 25 percent of the feature extracted samples. Both phases achieved 100 percent accuracy, correctly identifying all of the damaged and undamaged samples, as shown in the confusion matrix of Figure 10.

These results provide a benchmark to compare with the SNN accuracy.

4.2 SNN

The QUGS feature extracted data is represented as numerical numbers. To enable the development of an SNN the data must first be encoded into spike trains which represent a frequency, in order to be used as input data.

Using PyCharm with a python package called BindsNet, the selection of a new encoding scheme was required to best reflect the varied data. The data spanned over a large range of frequencies between approximately 15Hz – 475Hz. To make this range smaller a banding system was created, dividing the data into 10Hz wide bands comprising of 47 in total. As the band intervals increase in size, so do the length of the spike trains, adding additional spikes to each band, making each one larger than previous. The total spike trains are repeated to provide a 1-second duration of stimulus, i.e. to achieve an appropriate length of input stimulus for the SNN.

The SNN consisted of 30 neurons in the input layer (one neuron per joint in the dataset) and 2 output LIF neurons: *undamaged*, *damaged.* The SNN is a fully connected network and uses the Spike-Timing Dependant Plasticity (STDP) learning algorithm.

The network was able to achieve an accuracy level of 87.5 percent and was able to identify all of the undamaged samples and majority of the damaged samples, when trained on 75 percent and tested on 25 percent of the feature extracted data. An equal amount of damaged and undamaged samples were used in both the training/testing groups. Comparative work has been conducted by Zanatta et al, achieving an 88 percent accuracy level in comparison to the 87.5 percent accuracy level from this research (Zanatta et al, 2021). However, the comparative network is a Long Short-Term SNN (LSNN) and is significantly more complex with recurrent neurons, and also in neuron density with between 50 to 500 input neurons, 20 recurrent neurons and 2 output neurons (Zanatta et al, 2021).

The proposed SNN was created to determine if the QUGS data could be classified correctly, as the vision for this work is to incorporate a self-repair element, in the form of an artificial astrocyte cell into the SNN network, providing the additional capability to tolerate failure. Rapid decision-making was not the aim of this research but is ultimately a focus of future work.

4.3 Comparing SNN Against ANN

The ANN proved to have overall, a better level of accuracy of 100 percent identifying all of the damaged and undamaged structural health states correctly, in comparison to the SNN which classified 87.5 percent of the samples correctly. This is demonstrated in Table 2.

Table 2: Displays the results comparing the accuracy of the ANN and SNN, when trained on 75 percent and tested on 25 percent of the data.

Network Type	Data Split (%)		Accuracy (%)
	Training	Testing	
ANN	75	25	100
SNN	75	25	87.5

The ANN results provide good benchmark data and was expected to have a higher level of accuracy compared to the SNN. This is because ANNs are well established and not overly complex.

However, when considering the application of SHM require low power and compact edge computing capabilities, SNNs can achieve must lower area/power performances than ANN equivalents (Yang et al. 2021). There is a trade-off between high accuracy/high-compute overheads and meeting lower-power budgets but with a reduction in accuracy.

SNNs are more complex but possess the ability to incorporate a self-repair element into the network; ANNs do not have this capability. This network sets the foundation for future research.

5 CONCLUSION AND FUTURE WORK

Feature extraction is a key step when developing structural health applications and working with large datasets. Based on this work, it is evident that there are particular features that suit bespoke datasets better than others. FFT demonstrated to be the superior feature in the QUGS dataset. This contributed to the overall accuracy results achieved by the ANN and SNN, as the input data was more discernible between damaged and undamaged samples than displayed in the raw data. This, therefore, aided data classification.

Future work could involve incorporating the use of ensembles to further improve the accuracy and performance of the SNN. However, the main goal is to develop the SNN further by creating an astrocyte-neuron network (SANN), that can monitor and classify structural damage as well as realising self-repairing capabilities (Liu et al 2017). Upon achieving a good level of accuracy, the intention is to implement the network in FPGA hardware, where the systems performance will be benchmarked against conventional methods and evaluated, in terms of reliability and accuracy. This should enable large man-made structures to be monitored for long periods of time, without human intervention.

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