ARTIFICIAL NEURAL NETWORK-INTEGRATED BUILDING INFORMATION MODELLING FOR ENHANCED POST-DISASTER DAMAGE DETECTION AND VISUALIZATION

FINAL YEAR PROJECT UG 2019

by

SAAD SHAHID YAQOOB (G.L.)	321876
IBTESAM ASHJHA	321672
SANAN AHMED	291569
SHAHROZ MALIK	295302

NUST Institute of Civil Engineering (NICE)

School of Civil and Environmental Engineering (SCEE)

National University of Sciences and Technology (NUST), Islamabad, Pakistan

2023

This is to certify that the

Final Year Project Titled

ARTIFICIAL NEURAL NETWORK-INTEGRATED BUILDING INFORMATION MODELLING FOR ENHANCED POST-DISASTER DAMAGE DETECTION AND VISUALIZATION

Submitted by

SAAD SHAHID YAQOOB (G.L.)	321876
IBTESAM ASHJHA	321672
SANAN AHMED	291569
SHAHROZ MALIK	295302

has been accepted towards the requirements for the undergraduate degree

in

CIVIL ENGINEERING

____

Dr. Muhammad Usman Hassan
Assistant Professor
NUST Institute of Civil Engineering (NICE)
School of Civil and Environmental Engineering (SCEE)
National University of Sciences and Technology (NUST), Islamabad, Pakistan

This thesis is dedicated to our parents.

For their love, support and prayers throughout our lives.

ACKNOWLEDGEMENTS

First and foremost, we would like to thank our Creator Allah the Almighty, for without His blessings, this project would not be complete.

We would like to express our deep and sincere gratitude to our research advisor, Dr. Muhammad Usman Hassan, without whom this work would not have been possible. His understanding, encouragement, and personal guidance have provided a good basis for the present thesis. His wide knowledge and logical way of thinking have been of great value for our project. We would like to thank him for giving us the opportunity to carry out this research and for his patience, guidance, and support throughout our journey in making this project a reality.

Finally, we would like to acknowledge the contribution of our colleagues, who provided us with moral and intellectual support throughout this journey. We would also like to thank the laboratory staff at NICE, whose support in the background has been crucial.

ABSTRACT

This report presents a unique approach to Structural Health Monitoring (SHM) using Artificial Neural Networks (ANNs) and Building Information Modelling (BIM), designed to provide real-time damage indices as indicators of structural health. First and foremost, this research is aimed at developing resilient infrastructure in regions susceptible to natural calamities, specifically earthquakes and floods. The approach presented herein integrates advanced sensor technology and machine learning to innovate traditional SHM methods.

The study first explores the data acquisition process, where an ADXL345 sensor is employed to collect acceleration data from a structure. The raw data undergoes various stages of feature extraction including detrending, filtering, Fourier Transform, frequency extraction, and calculation of mode shape coefficients. The processed data then feeds into an ANN model, which predicts the damage index, an essential parameter in SHM.

The validity and robustness of the proposed methodology were confirmed through comprehensive validation, involving a case study of a bridge. Furthermore, the SHM system's integration with Autodesk Revit software allows for intuitive visualization of damage indices on the building model, thus paving the way for informed decision-making.

In summary, this research has laid down a strong and versatile foundation for real-time SHM. While the focus in this research has been restricted to buildings and bridges, the developed methodology and system are adaptable to other structures, marking a significant advancement in the future of SHM.

Keywords: Structural Health Monitoring, Artificial Neural Network, Damage Index, Mode Shape Coefficients, Real-time Monitoring, Post-Disaster Damage Assessment, IoT in Structural Engineering, Building Information Modelling (BIM).

TABLE OF CONTENTS

List of Figures

List of Tables

CHAPTER 1

INTRODUCTION

1.1 Background

Civil structures and infrastructures have a significant impact on the economy and are essential for the daily lives of people worldwide. However, these assets often experience early damage and approach the end of their lifespan. Replacing such structures would require a considerable amount of resources in terms of cost and labour, which may exceed the available financial and human resources (Balageas, Fritzen and Güemes, 2010). Furthermore, natural disasters such as earthquakes and floods can damage these structures. In the time of damage, there is a need for quick decision-making on behalf of the authorities as they need to find out if the structures are habitable or not and if displaced people can be allowed to return.

Visual Inspection is a commonly used method as a part of this process. However, it is labour-demanding and time-intensive as field staff are required to examine each item on the checklist individually. Often, this involves dismantling secondary components to reach the load-bearing structural elements (Liu, D. et al., 2019; Balageas, et al., 2010). Additionally, this method lacks efficiency, is infeasible, and does not provide quantifiable details about internal defects within the structural member. Furthermore, the detection of damage depends significantly on the judgement of the inspector. The issue with such techniques is that they result in unpredictability and unreliability when assessing the health of a structure (Ghosh et al., 2020).

Structural health monitoring (SHM) is a field of science that focuses its efforts on evaluating and monitoring the integrity of a structure of interest. It consists of implementing a scheme of monitoring the structure, for example, using periodically spaced dynamic response measurements, extracting sensitive damage-related features from these measurements, and then performing statistical analyses to determine the system's actual state of health (Brownjohn, 2006).

While local Non-Destructive Evaluation (NDE) tools have traditionally been used for monitoring, recent research has focused on global monitoring using permanently installed sensors. This has resulted in increased interest in SHM due to its potential for significant life-safety and economic benefits (Farrar and Worden, 2007).

1.2 Research Significance

Manufacturing organizations around the world want to detect damage in their products at the earliest possible instance. To do that, these organizations have to perform one or another form of SHM and are driven by the prospective life-safety and economic benefits of this technology. SHM has the potential to reduce the unpredictability attached with construction process and notably lessen the economic and human losses incurred during a seismic activity. In addition to that, many components of the technical infrastructure are nearing the end of their actual design life. Due to financial constraints, the use of these structures is exceeding their design life and, in this scenario, the ability to constantly monitor these structures is becoming extremely crucial.

Almost all current structural maintenance is being done in a time-based mode. With SHM, it will become possible for the current maintenance practices to evolve into cost-effective condition-based maintenance philosophies. This will entail a sensing system that notifies the operator that damage has been detected in a structure. However, life-safety and economic advantage will only be gained if the proposed SHM provides sufficient warning in a timely fashion so that corrective measures can be taken before damage turns into failure. This requires complicated monitoring hardware to be attached to the system and an equally compatible data analysis process to interrogate the structure. It is also important that the monitoring system being used is at least as accurate as the structure or the target system.

Apart from this, SHM has the potential of increasing the time intervals between scheduled maintenance and enable the equipment to stay in the field for a longer period and generate revenue in the time it would otherwise take for it to be taken back to the manufacturer for inspection.

The topic of SHM is of interest to a wide range of industries and government agencies. Several technical disciplines, however, need to be integrated to properly address SHM problem. Finally, the initiation of specialized courses on SHM technologies and methodologies is attestation to the keenness expressed by the industry.

1.3 Problem Statement

Pakistan has been a victim of multiple natural disasters in the past including floods and earthquakes. Rendered homeless, millions were affected. Current damage detection techniques include visual inspections. However, visual inspections are time-consuming and costly, therefore they are not suitable for post-disaster scenarios (Liu, D. et al, 2019). Hence, there is a need to develop a technique that makes post-disaster damage detection quick and cost-effective.

The aim of this research is to develop an accurate and efficient real-time SHM system using an ANN-based machine learning model integrated with Building Information Modelling (BIM). The system will be designed to monitor multi-storey buildings and provide real-time visualization for potential structural damage or failure. The research will contribute to the development of cost-effective and reliable SHM systems that can improve infrastructure safety, reduce maintenance costs, and improve disaster response.

1.4 Objectives

There are three main objectives of this study. These are:

- To develop an integrated solution that combines BIM and machine learning techniques for real-time damage detection and visualization.
- To explore the potential of accelerometer data as input for the machine learning algorithm to accurately detect and predict damage in buildings.
- To investigate the effectiveness of the proposed solution in detecting and visualizing different types of damage in different building materials and structures.

1.5 Scope of Work

The research aims at the development of a cost-effective prototype that includes an end-to-end solution for structural health monitoring of concrete buildings. Data acquisition will be carried out using accelerometers and will be transmitted and processed using microprocessors connected to WiFi. The identification of damage will be carried out using an ANN-based machine learning model. Finally, the damage will be visualized in the form of highlighted elements on the Building Information Model on Revit.

1.6 Overview of Chapters

Chapter 2 – **Literature Review** offers a comprehensive overview of existing knowledge in this field, as well as the application of machine learning techniques, notably artificial neural networks, in this domain.

Chapter 3 – Methodology we introduce our unique approach which combines real-time acceleration data acquisition, feature extraction, machine learning data processing, and damage visualization. The specific hardware and software used, the machine learning model designed, and the signal processing techniques applied are all discussed in detail.

Chapter 4 – Results and Validation presents the results of the trained model, which includes a thorough validation against a specific case study. This chapter also features a detailed discussion on the accuracy, effectiveness, and reliability of our model.

Chapter 5 - Conclusion contains the conclusion of the study.

CHAPTER 2

LITERATURE REVIEW

2.1 Structural Health Monitoring

2.1.1 Structural Health Monitoring

The procedure of executing identification of damage in infrastructure is known as Structural health monitoring. For this purpose, a number of tools are available for Non-Destructive Evaluation (NDE). However, in recent years, a large number of SHM research has tried to identify damage on a global scale by use of permanently installed sensors in structures.

Damage is widely understood as changes in any system which negatively impact its present or future health and performance. This implies that there has to be a comparison between two different states out of which one is considered the initial/undamaged state. Another note is that the term damage does not equal the total failure of the structure: rather, it means that the structure is not performing its function in its optimal manner.

Structural Health Monitoring (SHM) is the process of using various sensors and analytical tools to monitor the structural condition of a system continuously or periodically, such as a building, bridge, or aircraft, to detect and assess any damage, degradation, or abnormalities, and provide early warning and information for maintenance, repair, and safety purposes.

Identification of damage in structures is done by making use of five closely related fields which are:

- Structural Health Monitoring
- Condition Monitoring
- Non-Destructive Evaluation
- Statistical Process Control
- Damage Prognosis.

Traditionally, SHM (Worden and Dulieu-Barton, 2004) is synonymous with on-line, global damage identification in structures. Condition Monitoring (Bently and Hatch, 2003) is comparable in certain respects to SHM, but is used for damage detection in rotating machinery such as used in power generation. Non-Destructive Evaluation (Shull, 2002) is typically carried out off-line and is primarily used for characterization of damage and check for its severity when there is a *prior* knowledge of the location of damage. Statistical Process Control (Montgomery, 1997) is process-based and uses different types of sensors to monitor changes in a process. Damage Prognosis (Farrar et al. 2001, 2003) is used to predict the remaining operational life of a structure *after* the damage has been detected.

There are numerous challenges to integration of SHM: development of a process to define the optimal number and placement of sensors, identification of aspects which are sensitive to minor levels of damage, the capacity to differentiate between changes caused by test conditions or by natural conditions, development of statistical models to differentiate features from damaged and undamaged conditions and performing a comparative study of various methods of identifying damage.

The data acquisition part of SHM consists of selection of sensor types, excitation methods, number and location, and the storage hardware. This program is specific to applications. As a general rule, it is not possible to remove all sources causing variation in the data. So, we use the method of **data cleansing**. Data cleansing is the process of selecting certain data to pass on while removing others from the feature selection process. In this regard, filtering and re-sampling (signal processing techniques) can be considered as data cleansing methods.

Arguably, the part of SHM process that has received least attention is the development of statistical models for differentiation between features of damaged and undamaged structures. Statistical modelling has to do with the implementation of algorithms that operate on extracted features that express the state of damage of a structure in quantifiable data. The algorithms either contain examples from damaged structure, called *supervised learning*, or they are without examples from the damaged structure and are *unsupervised learning* algorithms. For engineering structures, unsupervised learning algorithms become the only viable option as it is not possible to damage structures to create data for supervised learning.

2.1.2 Damage Classification in SHM

The damage identification process can be summarized in a systematic structure (Rytter, 2003): **existence, location, type, extent, prognosis**. In a statistical model, usually the unsupervised learning model tells us about the existence and location of damage. Statistical models are also necessary to reduce false indications of damage. The following tables gives a summary of the various levels of damage detection and their description.

LEVEL	*DESCRIPTION*
Existence	This is the indicator of whether the damage is present in a structure or not. Even though most sensors and algorithms are very adept at deducing whether damage exists or not, there can be an occurrence of false positive or negative.
Location	After it has been ascertained that damage is present in a structure, its location is determined. This can be a complex task as depending on the sensors and the algorithm being used, the location determined can either be global or local.
Type	This is the kind of damage the structure has experienced. This includes foundation damage, cracks, water damage, fire damage, wind and storm damage, earthquakes, impact damage, fatigue damage, corrosion damage, chemical damage, etc.
Extent	This is the degree to which the damage has spread or to which it has affected the health of the structure. It can vary from low to high.
Prognosis	This is the result after a careful analysis of the above four. It tells us the overall health of the structure and what level of service can be expected from it in the future.

Table 1 Levels of Damage Classification in SHM

2.1.3 Challenges faced in SHM

The first challenge faced in SHM is perhaps that damage is generally at a local level and might not have a notable impact on the global low-frequency response (which is usually measured during SHM process). Secondly, feature selection and identification of damage in structure must be performed by the unsupervised learning mode of the algorithm because the data from damaged systems is not available. Lastly, an important challenge is to predict the required properties of the sensing systems before they have been deployed, and to ascertain whether the sensors themselves are in any danger of damage after deployment in the field.

2.2 Machine Learning in SHM

Machine Learning (ML) is the latest and most advanced tool in structural health monitoring. It is used to make the monitoring process independent in training itself using various techniques and tools in order to accurately predict the damage and in some cases, the extent, in the structure. There are two methods of ML, supervised and unsupervised. Supervised learning is a subclass of ML. It uses labelled datasets to train algorithms which, in turn, are used to classify data or predict the outcomes of an event accurately. Supervised learning uses data sets to train models to reach certain outcomes. Unsupervised learning, on the other hand, uses ML algorithms to analyze and group together the unlabeled datasets. Unsupervised learning discovers patterns and data groupings without the need for human interference. This mode of learning is used mainly for clustering, association, and dimensionality reduction (reducing the number of inputs while preserving the integrity of datasets).

2.3 Current Practices for ML in SHM

Some of the machine learning models applied in SHM previously are discussed below. Our discussion will mainly focus on the following supervised ML techniques:

- Artificial Neural Networks (ANN)
- Convolutional Neural Network (CNN)
- Support Vector Machines (SVM)

2.3.1 Artificial Neural Network (ANN)

Artificial Neural Network (ANN) is the most common and well-known ML algorithm used for supervised learning. ANN is predominantly applied in problems related to classification and regression. The structure of ANN is such that it comprises of an input layer, hidden layer(s) depending on the nature and complexity of the algorithm, and an output layer. Datasets are provided for the training of ANN systems and then using those, the supervised models in SHM process perform damage detection, localization, and severity estimation.

Some of the ANN techniques used in ML for SHM are listed below:

- In Tan, Z.X. et al., (2019), the authors proposed ANN architectures for damage detection and localization in different structures. For this purpose, an experimental model of a multiple steel girder composite bridge was tested. The ANN techniques used was **LMBP.**
- In Padil, K.H. et al., (2020), presence of damage was identified with respect to multiple variables and uncertainties. A simply supported steel truss bridge finite element (FE) model was tested. The ANN techniques used was **LMBP.**
- In Mousavi, A.A., et al., (2020), the presence, location and severity of bridge damage was identified. A fourteen-bay steel truss bridge experimental model was used for this paper. The ANN technique implemented for this was **BP.**

- In Finotti, R.P., et al., (2019), statistical indicators were used to detect changes in structures. A simply supported beam FE model and railway bridge experimental models were tested in this study. The ANN techniques used here is **LMBP.**
- In Chang, C.M., et al., (2018), the study was focused on identification of presence, location and severity of damage in a building. A twin-tower building experimental model was studied in this research. The ANN technique used here is **BP.**
- In Geng, X., et al., (2018), the research was directed towards identification of presence and the type of damage in plate. For this, a carbon fiber-reinforced plastic plate was used. The ANN technique used in this study is **BP.**
- In Morfidis, K., et al., (2017), damage sensitive features were proposed for the purpose of improving ANN structural damage prediction. For this study, numerical models of 30 reinforced concrete buildings were used. The ANN technique used was **LMBP**, along with **SCG.**
- In Padil, K.H. et al., (2017), presence of damage in a structure was identified using noisy ANN training data. A single-span steel frame numerical model was studied for this research. The ANN technique used in this research was **LMBP.**
- In Jin, C., et al., (2016), a damage detection method was proposed using ANN and EKF for structures under temperature changes. A Meriden bridge FE model was adopted for this study. The ANN technique used was **BP.**
- In Dworakowski, Z., et al., (2016), an ensemble design method for ANN hyperparameter selection was proposed. For this research, an instrumented aircraft panel and an instrumented wind turbine were studied. The ANN algorithm used was not specified.
- In Ng, C.T., (2014), a Bayesian model class selection method was proposed to select optimal ANN hyperparameters. The Phase 2 IASC-ASCE SHM benchmark structure FE model was used. The ANN algorithm used was not specified.
- In Min, J., et al., (2012), an NN technique was reported which could be used to select damage-sensitive frequency ranges and diagnose structural damage. The study was carried out on an aluminum beam experimental model. The ANN technique adopted for this research was **BP.**
- In Mardiyono, M., et al., (2012), an SHM system based on ANN was proposed to predict the building damage index. For this study, a building FE model was used. The ANN technique/algorithm used in this research was **BP.**

2.3.2 Convolutional Neural Network (CNN)

The Convolutional Neural Network (CNN), perhaps the most commonly used deep AI algorithm, has found applications across numerous data-based classification fields and regression-related problems (Gomez-Cabrera, A., et al, 2022). A standard CNN comprises three distinct layer types based on the specific functions they perform. These include convolutional layers, pooling layers, and fully connected layers. Convolutional layers undertake the automatic feature extraction from the input data, while pooling layers help reduce the size of the data. On the other hand, fully connected layers handle data classification. CNN design architecture allows for stacking numerous layers to elevate the network's complexity. However, an increase in the number of layers implies an increase in computational training time and resource usage during computations. Some techniques used in CNN are:

- In Sony, S., et al., (2022), a 1D-CNN for multiclass structural damage detection using limited datasets was proposed. The research was conducted on a Z24 bridge experimental model.
- In Zhang, R., et al., (2020), a CNN architecture was proposed to develop a surrogate model for modelling the seismic response of the building structures. For this study, a six-storey hotel instrumented building was used.

2.3.3 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a much-preferred machine learning algorithm often employed for solving classification and regression issues. The maximization objective within SVM can be interpreted as an optimization problem, and various methods can be applied to solve it. However, the SVM training phase can be computationally intensive and may not be a good fit for real-time SHM systems that rely on post-training enhancements and updates to the ML model (Gomez-Cabrera, A., et al, 2022). One way to mitigate the computational costs associated with SVM is to combine it with other signal processing techniques or damage-sensitive feature extraction methods. For instance, Cuong-Le et al, (2021) proposed an integration of Particle Swarm Optimization (PSO) and SVM for structural damage identification. They compared the performance of ANN, DNN, Adaptive Neuro-Fuzzy Inference System (ANFIS), and SVM. The combined PSO-SVM model exhibited the highest accuracy amongst the four ML algorithms tested and was successful in accurately predicting damage locations in validation tests.

2.4 Building Information Modelling (BIM)

Building Information Modelling (BIM) serves as the foundational element in the digital transformation sweeping across the architecture, engineering, and construction (AEC) industry. It provides a digital illustration of the physical and functional attributes of a building and facilitates its design, construction, and operation. The AEC industry widely embraces BIM due to its numerous advantages such as enhanced collaboration, reduction in errors and rework, and augmented efficiency. Nonetheless, its utilization within the field of structural health monitoring (SHM) is still in its nascent stages. This underdevelopment can be attributed to the SHM community's limited and gradual acceptance of the technology (Edirisinghe, et al., 2017).

Traditionally, a large number of software applications were used for building systems design, planning, documenting, drafting, designing, and structural analysis. These applications had no cohesion and there was no method which could be employed so that more than one software could work in sync to perform different tasks. This made the designing of a structure an extremely arduous, expensive and inefficient process. The unique advantage BIM has is the solution of all these problems under one single program. This integration of functionalities of different software into one application is the reason why 96% of professionals are in favor of implementing this technology in the construction industry here in Pakistan (Masood, et al., 2007). In this regard, Autodesk Revit is one of the most significant tools for BIM. This is because Revit treats any object in modelling as actual objects by giving them real-life qualities (Zolotova, et al., 2015).

The integration of BIM with SHM can be divided into four stages: the creation of an accurate model representation, sensor-based information collection, data storage, and linking the amassed data to the BIM model. The model should incorporate the virtual sensor's location and its parameters to aid engineers in visually locating the sensor effortlessly and to enhance data management (Valinejadshoubi, et al., 2019; Boddupalli, et al., 2018).

However, BIM is hindered by a limitation which is the lack of interoperability and data exchange with other software due to the absence of models that support efficient data transfer (Delgado et al., 2017). The Industry Foundation Class (IFC) serves as a standard data format for cross-platform data exchange, implying that the BIM model must be translated into an IFC file prior to interaction with other software such as SHM and Finite Element analysis software.

2.5 Internet of Things (IoT)

The phrase is composed of the words “Internet” and “Things” where internet is used to describe a system that connects different networks of computers whereas the word Things are the objects which can help in sensing and collection of data about their environment. So, Internet of Things can be defined as a universal mechanism using an IP suite in which objects or “things” having an identity work in a smart environment while being effortlessly interconnected into the network of information and are equipped with sensors or RFID tags. IoT is dependent on a variety of materials, technology, communication networks and infrastructural protocols.

Sensors are used for the collection and acquirement of data in real time over the internet to a data storage. The purpose is to enable the end user to remotely access the devices using the Internet. However, like other computational models and services, IoT also faces constraints from computational usage and energy consumption. This is commonly mitigated by integrating different protocols and practices.

2.6 Feature Extraction

Feature extraction is a fundamental process in machine learning and pattern recognition that involves transforming raw data into a reduced and representative set of features. The aim is to extract meaningful and relevant information from the data while reducing its dimensionality. By selecting or creating informative features, feature extraction enhances the performance of machine learning algorithms, improving accuracy, efficiency, and generalization. Various techniques such as dimensionality reduction, statistical methods, transformations, feature selection, text mining, and deep learning methods are employed based on the nature of the data and the specific problem domain. These techniques allow for the extraction of essential characteristics from the data, enabling more effective analysis and modelling.

Some feature extraction techniques are:

1. **Dimensionality Reduction**: Techniques such as Principal Component Analysis (PCA) or Singular Value Decomposition (SVD) reduce the dimensionality of the data by identifying the most significant orthogonal features that capture the maximum variance in the data.

2. **Statistical Methods**: Statistical techniques like mean, standard deviation, median, or correlation coefficients can be used to summarize and extract relevant statistical features from the data.

3. **Transformations**: Data transformations like Fourier Transform, Wavelet Transform, or Discrete Cosine Transform can be applied to extract frequency or time-domain features from signals or images.

4. **Feature Selection**: Feature selection methods aim to identify the most informative subset of features from the original dataset. Techniques like Recursive Feature Elimination (RFE), Information Gain, or L1 regularization (Lasso) are commonly used for this purpose.

2.7 Summary of Research Gap

It was observed, however, that there is not currently a system in place which accurately sensed damage in structures, acquired and processed data in real time using ML, and then showed the damage present in the structure on a digital twin on BIM. This research gap is what we intend to cover through our experimentation and research.

CHAPTER 3

METHODOLOGY

The methodology can be broadly classified into three main phases: data acquisition, data processing, and data visualization.

1. **Data Acquisition:** The first stage in the system is data acquisition. For this, we utilized the ADXL345 accelerometer sensor and ESP32 microcontroller. The acceleration data collected was wirelessly transmitted to a computer in real-time, facilitating an effective and efficient monitoring system.
2. **Data Processing:** Once the acceleration data was acquired, the next step was feature extraction. In this phase, we employed various signal processing techniques to obtain the necessary parameters. Then, we employed an Artificial Neural Network (ANN) model. We fed the ANN with inputs such as the fundamental frequency, mode shape coefficient, and storey height of the building, and trained it to predict the output, which was the damage index.
3. **Data Visualization:** The final stage was data visualization. The damage index output from the ANN model was used to visualize the damage distribution in a 3D BIM model in Revit. This step was critical in visualizing the potential structural damage areas, enabling engineers and decision-makers to better understand the extent and nature of the damage.

The complete system architecture is illustrated in the figure below.

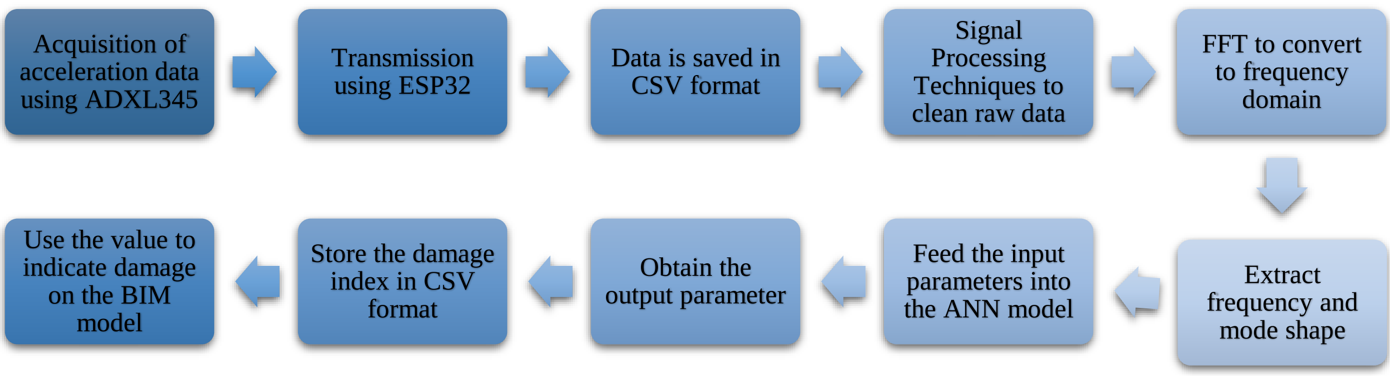

Figure 1 Flowchart describing the opted methodology

3.1 Data Acquisition

Damage detection of the SHM system relies heavily on the accuracy and resolution of the data collected. Therefore, an accurate and robust data acquisition setup is required.

3.1.1 Selection of Damage Indicator

For our purposes, acceleration was chosen as the damage indicator to be measured and analysed. The reasons for choosing acceleration are as follows:

- Response to dynamic forces: Structures experience dynamic forces, such as those caused by earthquakes, wind, and traffic loads. Acceleration data captures the response of the structure to these forces, providing valuable information about its behaviour and integrity.
- Mode shapes and frequencies: Acceleration data can be used to determine the mode shapes and frequencies of a structure, which are essential parameters in structural health monitoring. Changes in these parameters can indicate the presence of damage or structural degradation.
- Sensitivity to damage: Acceleration data is sensitive to local damage and global changes in the structure. Even small changes in the stiffness or mass distribution of a structure can lead to noticeable variations in acceleration response, making it a suitable input for damage detection algorithms.
- Ease of measurement: Accelerometers are widely available, relatively inexpensive, and easy to install on structures. They provide accurate and reliable measurements of acceleration, making them a popular choice for structural health monitoring applications.
- Compatibility with ML algorithms: Acceleration data is compatible with various machine learning algorithms, including the one you used in our project. The data can be processed and transformed into meaningful features, allowing the ML model to learn patterns and relationships that can be used for damage detection.
- Real-time monitoring: Acceleration data can be collected and transmitted in real-time, enabling the continuous monitoring of structures and the timely detection of damage. This is particularly important in post-disaster scenarios or for assessing the integrity of aging structures.

3.1.2 Hardware

The hardware that was employed for our data collection process consists of two key components: the ADXL345 accelerometer sensor and the ESP32 microcontroller. The ADXL345 sensor is a high-precision micro-electro-mechanical system (MEMS) accelerometer that measures three-axis acceleration of the structure. It is known for its high resolution and measurement accuracy, making it an ideal choice for our project. The other options we have for MEMS accelerometers are the ADXL335 and the ADXL 355. ADXL 355 was not available locally, therefore, it wasn’t shortlisted. ADXL 335 was not chosen due to its inferior performance compared to the ADXL 345 accelerometer, including the data range, power consumption and data display.

The ESP32 microcontroller functions as the control unit of our system, managing the data received from the sensor, and transmitting it wirelessly to the data processing unit. The ESP32 was chosen for its high performance, integrated Wi-Fi capabilities, and compatibility with various development environments, thus perfectly aligning with our need for real-time data acquisition.

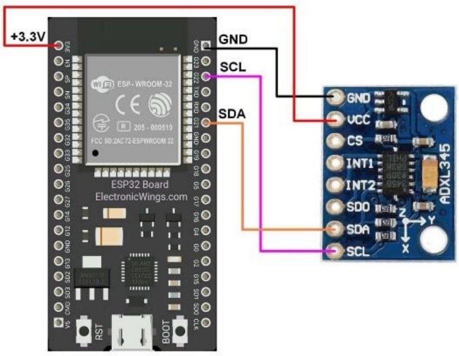

Figure 2 Hardware Connections

3.1.3 Programming

On the software front, the ESP32 microcontroller was programmed using the Arduino IDE. A specific script was developed that commands the microcontroller to gather acceleration data from the ADXL345 sensor, process it, and then wirelessly transmit this data to a computing device in real-time. At the receiving end, a Python-based script was established to receive this data, and concurrently store it into a .csv file. This process facilitates real-time data acquisition, a feature that is absolutely vital to ensure that our SHM system is working with the most current data, which in turn is critical for effective monitoring and timely damage detection.

In conclusion, the meticulously designed data acquisition setup, revolving around acceleration measurements, ensured a consistent flow of reliable data for subsequent processing and analysis by our machine learning models.

3.2 Data Processing

Once the data is collected, it has to be processed to obtain meaningful information regarding the damage present in the structure. The data processing involves two major steps: feature extraction to obtain the necessary parameters and processing using the ANN algorithm.

3.2.1 Feature Extraction

Feature extraction is a crucial step in our structural health monitoring (SHM) project. This step involves transforming raw data into a set of features that represent the core attributes of the data, which can be used to train our machine learning models for damage detection. We have implemented a process that includes several key steps: detrending, filtering, performing a Fourier Transform, extracting the frequency, and calculating the mode shape coefficient. The coding for this process was done on a Python script. The acceleration data collected from the sensor, which was stored in a csv file, is passed through the following steps.

1. The first step, detrending, is carried out to remove any trend present in our acceleration data that may be due to factors such as sensor drift. By applying the detrend function, we ensure that the data has a mean of zero, eliminating any linear trend from the data. This is essential to remove low-frequency components not related to the vibrational characteristics of the building structure.
2. Next, we implement a low-pass Butterworth filter. Filtering is an important step in signal processing, allowing us to eliminate high-frequency noise that is not relevant to the dynamics of the structure. The data is passed through a 2^{nd} order lowpass Butterworth filter with a normalized frequency cutoff limit of 0.5. This choice of a low-pass filter permits only low-frequency components (those that represent the building dynamics) to pass and suppresses components at higher frequencies (usually noise or other environmental influences).
3. After the acceleration data is cleaned, a Fourier Transform is applied to transform signals from the time domain into the frequency domain. The transformed data provides

the frequency content of the signal, which is necessary for the determination of natural frequencies. The frequency extraction step involves determining the dominant frequencies from the transformed signal. These frequencies correspond to the natural frequencies of the structure, which are fundamental characteristics that can be altered due to structural damage.

4. Finally, we calculate the mode shape coefficient using the obtained Fourier Transform results. Mode shapes represent the deformation pattern of a structure under vibration at specific frequencies. The mode shape coefficient is derived from the amplitudes of the Fourier Transform at the dominant frequencies.

Overall, feature extraction is a comprehensive process to transform raw acceleration data into meaningful information that can be used for damage detection in our SHM system. The two parameters that we derived are frequency and mode shape coefficient.

3.2.2 Defining Input and Output Parameters

Once the feature extraction is complete, the derived frequency and mode shape coefficient, along with the storey height, can be used as the input parameters for the ML model.

The output of the ML model is the stiffness damage index. This is a scalar value between 0 and 1 that gives an indication of the presence and severity of the damage on a multi-storey building. The stiffness damage index (Biddah et al., 1995) of the *i*th storey is defined as:

$$(\mathrm{DI})^i = 1 - \left(\frac{K^i_{\mathrm{final}}}{K^i_{\mathrm{initial}}}\right)$$

where:

$K^i_{initial}$ is the stiffness of the building in the undamaged state and,

K^i_{final} is the stiffness of the building in the damaged state.

K can be calculated as K = *base shear/storey drift*.

Damage state for structures can be defined as minor, moderate, severe, and collapse depending upon the value of damage index as given in Table 2 (Gunturi, 1996).

Damage States	*Range of proposed damage index*
Minor	0.0-0.15
Moderate (repairable)	0.15-0.3
Severe (irreparable)	0.3-0.8
Collapse	> 0.8

Table 2 Damage State corresponding to Damage Index

3.2.3 Model Architecture

Artificial Neural Networks (ANN) was chosen for our purposes due to its suitability for SHM because of the following characteristics:

- Adaptability: ANNs are capable of learning complex and non-linear relationships between input features and output predictions. This makes them well-suited for problems with complicated dynamics, such as structural damage detection and localization, where the relationships between the input features (story height, frequency, and mode shape coefficient) and the output (damage index) may be non-linear.
- Flexibility: The architecture of an ANN can be easily adjusted to accommodate various problem complexities. By tuning the number of layers, neurons, and activation functions, we can tailor the model to our specific problem, ensuring that it is neither underfitting nor overfitting the data.
- Robustness: ANNs can be relatively robust to noise and errors in the input data, which can be especially beneficial in the context of structural health monitoring, where measurement noise or environmental factors can affect the quality of the input features.

The architectural structure of the neural network was determined through a process of trial and error, aiming to reduce error margins and ensure rapid convergence. The final network comprised of three hidden layers along with the input and output layers. The input layer consists of three neurons corresponding to the input parameters: storey height, mode shape coefficient, and fundamental frequency. The output layer features one neuron representing the Damage Index (DI). Each of the hidden layers contains 30 neurons, and a nonlinear sigmoid function was employed as the activation function.

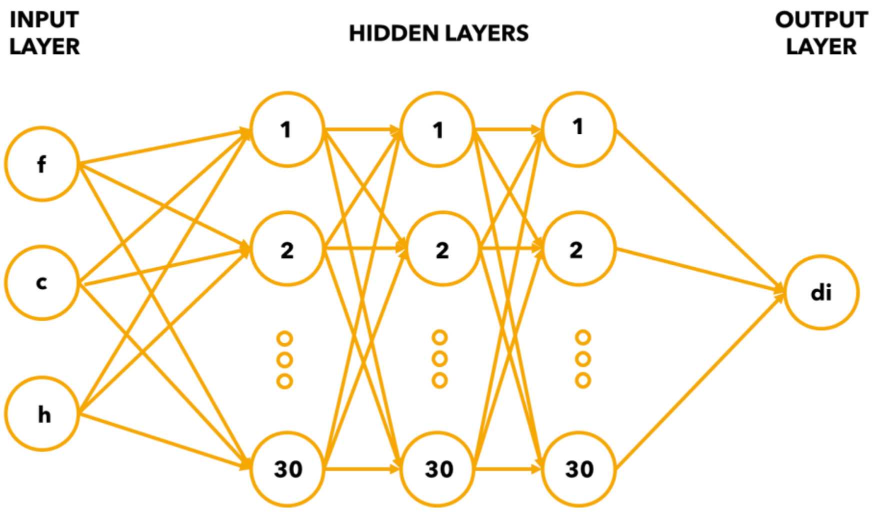

Figure 3 Architecture of ANN Model

3.2.4 Model Training

The training of our neural network was conducted using data acquired from STAAD Pro Analysis.

Kanwar et al. developed a model on STAAD Pro to simulate damage on 11 different scenarios and extract the required parameters accordingly. Since we have 11 different damage scenarios and three stories each, we obtained a set of 33 datapoints that were used to train and evaluate the model.

Input parameters for the network included storey height, mode shape coefficient, and fundamental frequency, while the output was the corresponding damage index (refer to Table 3). The trained network is thus designed to predict the damage index for frames that were not included in the initial training set.

For this study, we assumed training to be successful if the percentage errors between the experimental and ANN predicted values for all patterns are less than 10%. We excluded four patterns from the total data set for testing and prediction.

For training, we normalized all input and output data using a maximum value, ensuring that all values fell within the range of 0 to +1. This process was undertaken using a normalization factor specific to each parameter. The output from the network is hence a normalized output, which is transformed back to actual values by multiplying it by the normalization factor used during the training set preparation. Initial weights were randomly set within the range of -0.3 to +0.3.

Throughout the training process, the learning rate parameter and the momentum factor were kept constant at 0.15 and 0.85, respectively.

3.2.5 Model Evaluation

The following metrics were used to evaluate the model.

Evaluation Metric	Value
MSE	0.004
MAE	0.052
R^2	0.565

Table 3 Evaluation Metrics for ML Model

The following graph shows a comparison of the predicted values against the actual values.

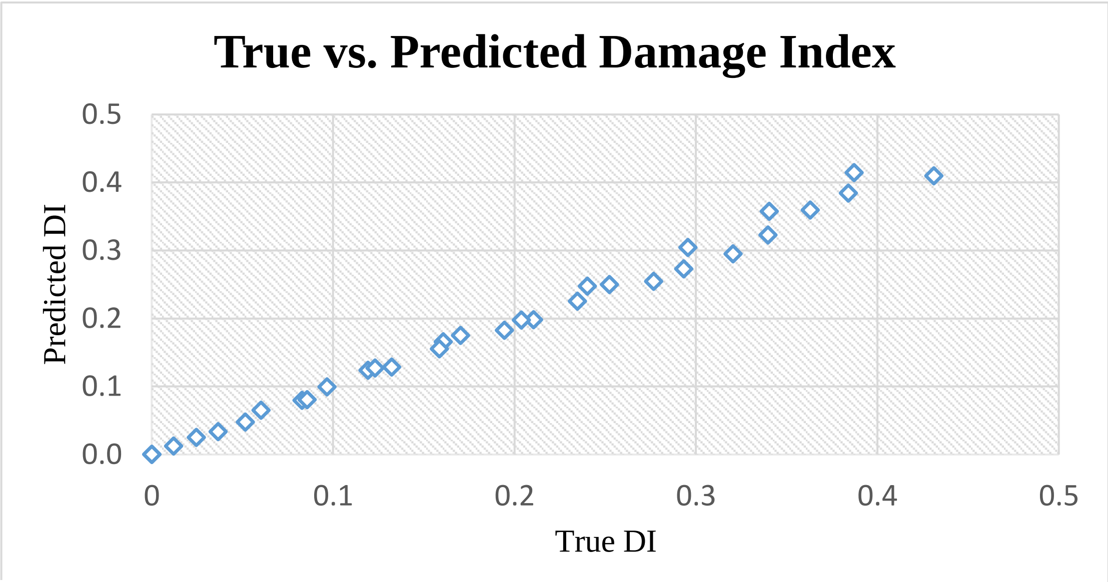

Figure 4 True vs. Predicted Damage Index Values

The dataset was used to train the network, with a target of minimizing the average mean square error between the required output and the network's output to less than 0.005. The effectiveness of the network was evaluated by comparing the network's output to the same input data set used for its training. It's evident from the plot that the predicted damage index values correspond accurately with the damage index values used in training the network, indicating successful training.

3.3 Data Visualization

Once the damage index is calculated, the damage (if present) is to be indicated on the digital twin. The following figure gives an overview of the visualization process:

Figure 5 Data Visualization Process

The most significant aspect of our data visualization process is the real-time updating of damage indices. These are stored in a CSV file that is updated continuously, thus facilitating real-time tracking of the building's structural health. The CSV file comprises two sections: the first cell (A1) is allocated for the latest damage index, whereas the chronological history of damage indices along with corresponding timestamps are logged in the cells below.

Furthermore, Autodesk Revit, a robust architectural design and documentation software application, is utilized to create a BIM model of our case study building. By integrating the system with Revit, we can map the damage index onto the building model. Changes in the colour on the building model correlate with the magnitude of the damage index, providing an immediate visual cue of the damage severity and location.

The following table shows damage state and the corresponding colour code.

Damage State	Range of Damage Index	Color Highlighted
Minor	0.00 – 0.15	Green
Moderate (Repairable)	0.16 – 0.30	Yellow
Severe (Irreparable)	0.31 – 0.80	Orange
Collapse	> 0.80	Red

Table 4 Color Codes corresponding to Damage State

The program utilizes two tools, namely Dynamo and PyRevit. Dynamo is a visual programming tool that extends the capabilities of Revit software. It provides an intuitive graphical interface for users to automate tasks without having to write traditional code. Users create scripts by connecting various nodes in a flowchart-like manner. PyRevit, on the other hand, is a Python-based scripting environment that runs on top of Revit. It provides a set of tools and an environment to write scripts in Python that interact with the Revit API. PyRevit is a powerful tool that enables users to automate complex tasks, customize the Revit user interface, and extend the functionality of Revit beyond what's possible with Dynamo or the built-in Revit macros.

The process works as follows. The script is designed to be run in Autodesk Revit using Dynamo, which is a visual scripting tool that works with Revit. The script is written in Python (via the Python Script node in Dynamo), utilizing the Python Revit (PyRevit) engine that allows interaction with the Autodesk Revit API (Application Programming Interface). This script interfaces with Revit to get data about building elements and change their visual appearance based on the given conditions.

The primary function of this script is to read a value from a CSV file, which is taken as the script's input. It then changes the color of selected building elements in the active view of the Revit model based on the value from the CSV file. Green, yellow, orange, or red colors are applied, depending on whether the input value falls within certain ranges. The colors are used to indicate different degrees of structural damage. Additionally, the script displays an alert message corresponding to the severity of the detected damage. The output of this script is the changed color of the elements in the Revit model and the alert messages. The script also returns the message "Script executed" to Dynamo, signifying its successful execution.

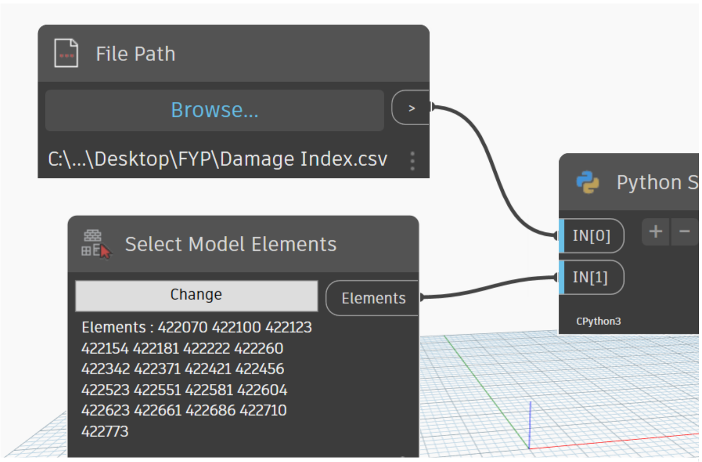

Figure 6 Dynamo Script

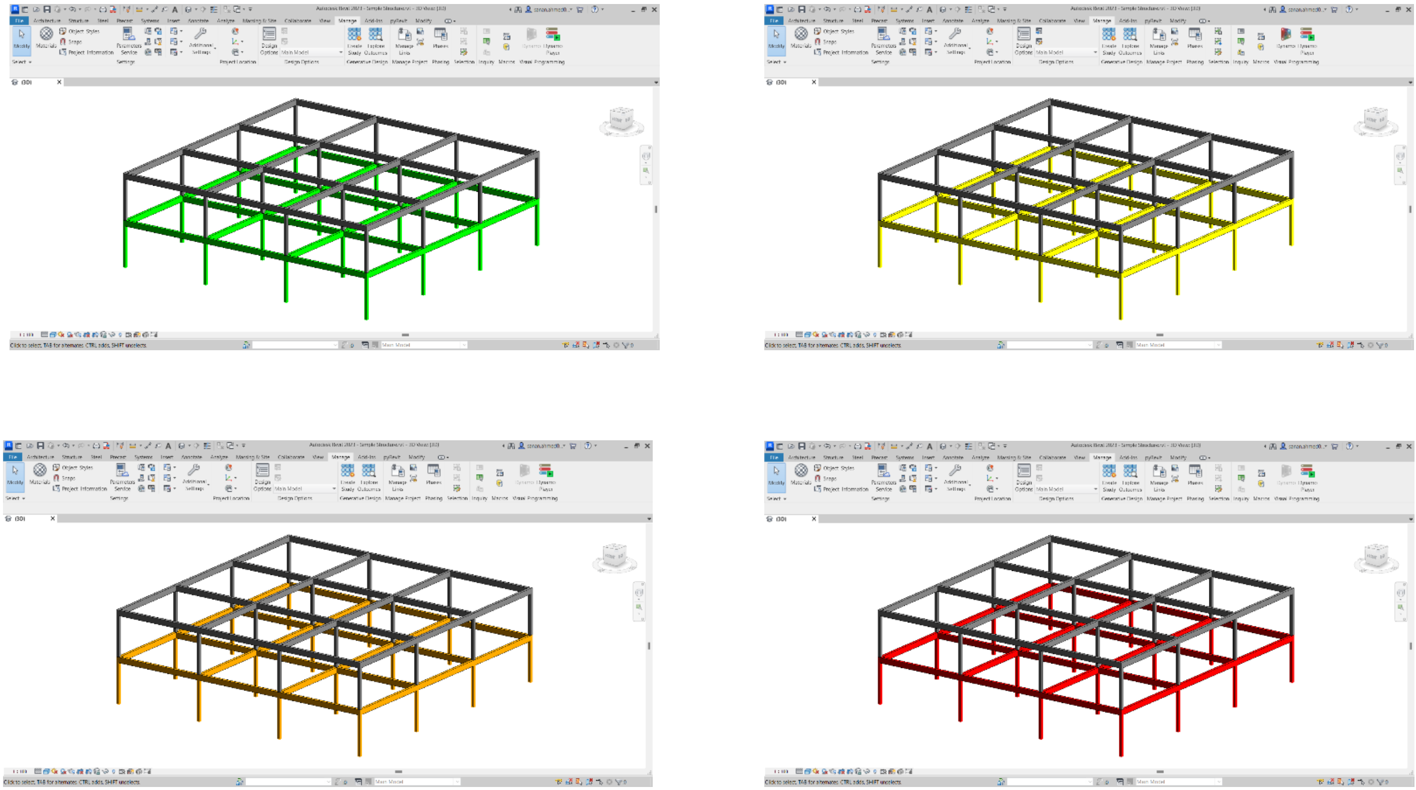

Figure 7 Damage States (a) Minor, (b) Moderate, (c) Severe and (d) Collapse

Figure 8 Warning Pop-ups (a) Moderate, (b) Severe and (c) Collapse Cases

CHAPTER 4

VALIDATION

It is extremely important that after a hypothesis has been formed or an experiment has been performed for the purpose of advancing a research theory, a real-world application of that hypothesis or experiment is also done to confirm that hypothesis. This real-world application of the hypothesis on any structure/material/object for confirmation of the results of the experiment is known as **validation of the results**.

4.1 Overview of Process

To validate the theory and results in our results, we performed a validation experiment on a bridge where there was a constant stream of traffic. The purpose of this validation experiment was to test the working of our system by using the raw acceleration data from the accelerometers. The accelerometers used in the validation experiment transmitted the raw data wirelessly for us to further process it into actionable input. The bridge on which the sensors were installed is built inside NUST and serves as a passage over a waterbody.

After the sensors were connected with the proper instruments and software, real-time raw data was collected from them. This was done to ensure that the data acquired from the sensors was as current as possible to monitor the health of the structure in real-time. The wireless transmission of the data was of great significance in this regard. The sensors were programmed to send numerous live readings over a set amount of time and the readings were then almost instantaneously processed to obtain the results.

Obtaining the results, as mentioned above, was made possible by integrating machine learning in our research. Machine learning is a complex field where the programs and machines are made to research and analyze the data automatically by using a machine learning model. In our research, we used Artificial Neural Network (ANN), a machine learning model which was most suited to our needs and the demands of the acquired data. ANN made it possible for the algorithm to process the raw data acquired from the accelerometers and present it in the form of a range between 0 and 1, which becomes the Damage Index.

This Damage Index was then analyzed by Revit. Revit is a software for making 3D renders of structures. Using an already existing model of the structure inside the software, the value of the damage index of the structural member would be evaluated and the software would be used to visualize the damage or its absence in the structure. This will be achieved by assigning a range between 0 and 1 to a certain color and if during the analysis the value of damage index fell between that range the structural member would be highlighted that color. This was significant because visualizing the health of the structure and the presence or absence of damage in such detail makes it extremely easy for technical professionals as well as non-technical professionals to fully understand the presence, location and extent of the damage.

4.2 Selection of Bridge

Figure 9 Picture of Selected Pedestrian Bridge

The bridge selected is a pedestrian bridge linking NUST Hostels with the cafeteria. The bridge is used by students everyday travelling from hostel to their respective departments and the Cafeteria C2. The bridge is a precast, double tee beam embedded in two supports. The beam is 9.8 m long and the dimensions are shown as follows.

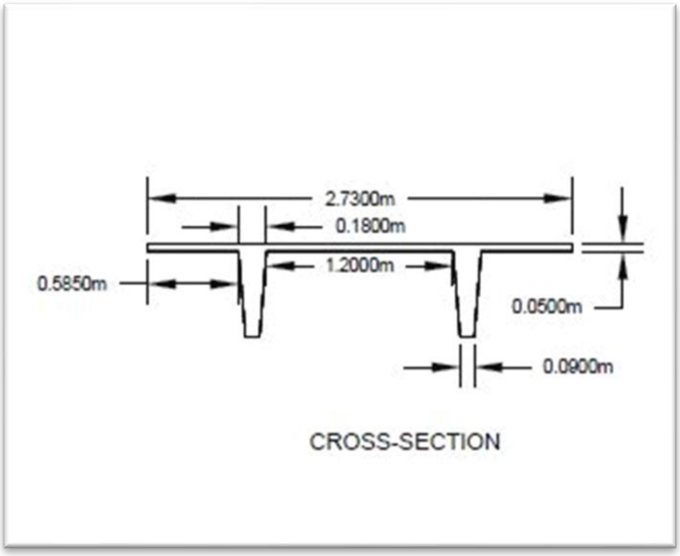

Figure 10 Cross Section of Pedestrian Bridge

4.3 Results and Discussion

The processed acceleration data is shown below, along with the Fourier Transform.

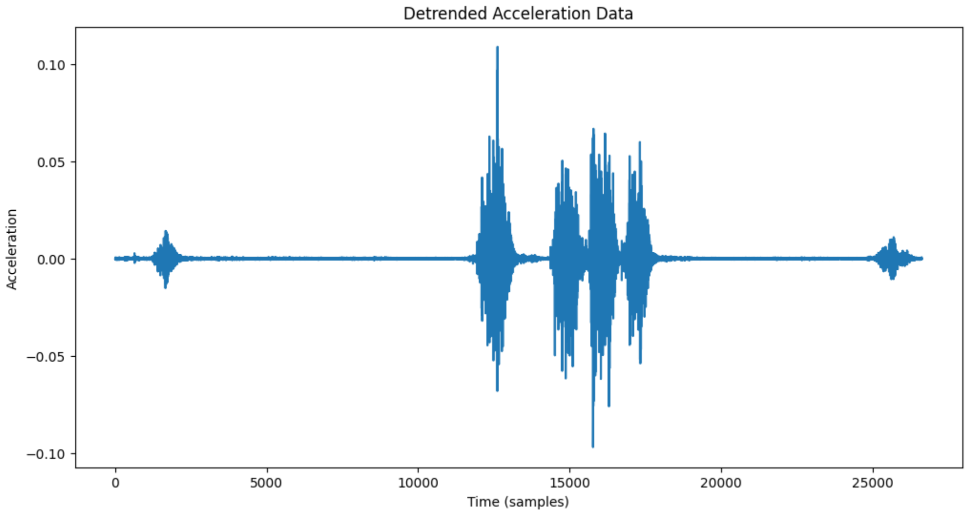

Figure 11 Detrended Acceleration Data

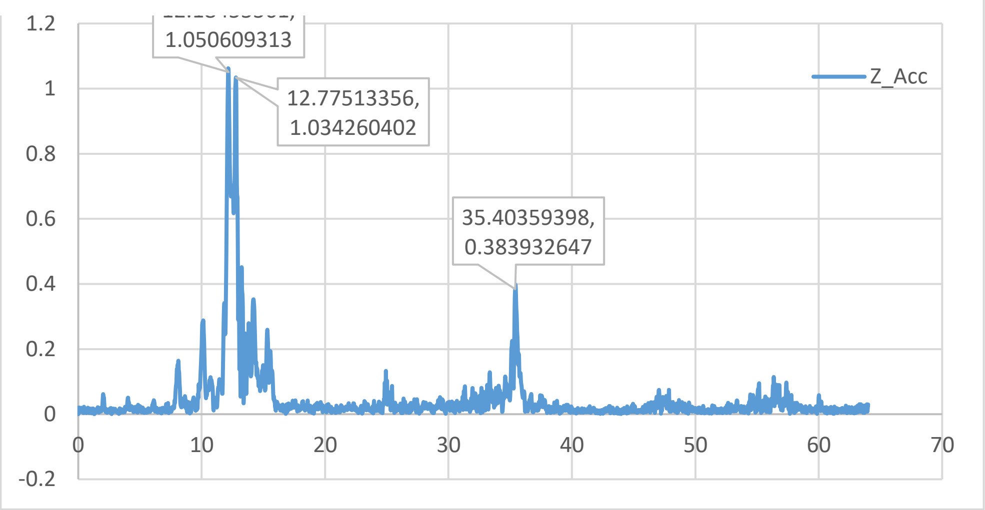

Figure 12 FFT Transform

The inputs to our ML model were as follows:

- Mode Shape Coefficient: 0.0179
- Frequency: 0.145
- Storey Height (assumed): 1

The following results were obtained using the data:

- Damage Index Obtained: 0.012
- Since, the damage index lies in the “Minor Damage” Range, no pop-up was generated on Revit.
- The structure was highlighted “Green”.

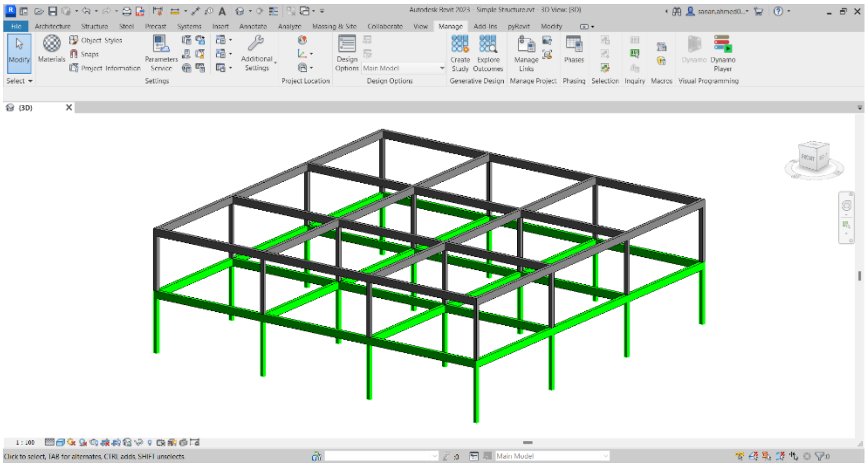

Figure 13 Colour-coding of structure

CHAPTER 5

CONCLUSION & RECOMMENDATIONS

5.1 Conclusion

This research has led to the development of an innovative Structural Health Monitoring (SHM) system employing Artificial Neural Networks (ANNs) for predicting the damage index in real-time. This system, which leverages the advancements in sensor technology and machine learning, provides a proactive approach to assessing the structural integrity of buildings, particularly in regions prone to natural disasters such as earthquakes and floods.

Throughout this study, we demonstrated that acceleration data, collected through an ADXL345 sensor, could serve as a reliable source for estimating the health of a structure. Our feature extraction process, involving detrending, filtering, Fourier Transform, and extraction of frequencies and mode shape coefficients, proved effective in extracting the required parameters from the raw acceleration data. The data processing step further solidified the robustness of our methodology, where an ANN model was utilized to predict the damage index, a critical indicator of structural health.

The reliability and accuracy of our system were demonstrated through the comprehensive validation process, which included a real-life pedestrian bridge. After applying our SHM system to the bridge, the system's working and effectiveness was reaffirmed.

Further, the integration of our system with Autodesk Revit amplified its usability by providing a visual representation of damage indices on the building model. This feature not only allows easy interpretation of the damage index but also facilitates informed decision-making.

In conclusion, this study underscores the potential of combining machine learning and BIM in SHM. While our focus has been on buildings and bridges, the methodology and system developed can be adapted to other structures as well, making this an exciting prospect for the future of SHM.

5.2 Potential Benefits

The system that we developed can have a significant impact in damage detection. Most notable benefits include:

- Saving time and costs associated with manual inspection.
- Saving the hassle of hiring specialized manpower for inspection.
- Having a better visualization of the structure for non-technical stakeholders (e.g., govt, investors etc.) which would facilitate quick decision-making.
- Storing and retrieving data more efficiently.

5.3 Future Recommendations

The research in this area can be further improved to discover more applications and fill other research gaps. Some of our recommendations include:

- Use sensors with a better sampling quality to obtain more reliable data.
- Enlarge the dataset using data augmentation techniques to improve the accuracy of the training of the model.
- Include temperature as a parameter, as this has a significant impact on the acceleration of the structure in different scenarios.
- Improve localization to specific element, because currently it is being done on storey-level.

REFERENCES

- Balageas, D., Fritzen, C.-P., & Güemes, A. (Eds.). (2006). *Structural Health Monitoring.* Wiley-ISTE.
- Bently, D.E., Hatch, C.T. & Grissom, B. (2002). *Fundamentals of Rotating Machinery Diagnostics.* ASME Press.
- Boddupalli, C., Sadhu, A. and Rezazadeh Azar, E. (2018). ‘An integrated structural health monitoring tool using building information modeling’. *6th International Structural Specialty Conference 2018, held as Part of the Canadian Society for Civil Engineering Annual Conference 2018,* pp.87–95.
- Boddupalli, Chanakya & Sadhu, Ayan & Azar, Ehsan & Pattyson, Scott. (2019). ‘Improved visualization of infrastructure monitoring data using building information modeling.’ *Structure and Infrastructure Engineering.* 15. 1-17. 10.1080/15732479.2019.1602150.
- Brownjohn, J. M. W. (2007). ‘Structural Health Monitoring of Civil Infrastructure.’ *Philosophical Transactions: Mathematical, Physical and Engineering Sciences*, 365(1851), 589–622.
- Chang, C.-M.; Lin, T.-K.; Chang, C.-W. (2018). ’Applications of neural network models for structural health monitoring based on derived modal properties.’ *Measurement*, 129, 457–470.
- Cuong-Le, T. et al. (2021). ‘An efficient approach for damage identification based on improved machine learning using PSO-SVM.’ *Eng. Comput*., 38, 3069–3084.
- Delgado, D. et al. (2016*). Management of structural monitoring data of bridges using BIM*. 10.17863/CAM.6377.
- Dworakowski, Z.; et al. (2016). ‘Ensemble ANN Classifier for Structural Health Monitoring.’ In *Artificial Intelligence and Soft Computing; Springer International Publishing*: Cham, Switzerland, 2016; pp. 81–90.
- Edirisinghe, R., et al. (2017). ‘Building information modelling for facility management : are we there yet?’ *Engineering, Construction And Architectural Management.*
- Farrar, C. R. (2003). *Damage prognosis: current status and future needs*. Los Alamos National Laboratory report LA-14051-MS.

- Farrar, C. R., Doebling, S. W. and Nix, D. A. (2001). *Vibration-based structural damage identification.* Phil Trans. R. Soc. A 359, 131-149.
- Farrar, C.R. and Worden, K. (2007). *An Introduction to Structural Health Monitoring.* Philosophical Transactions of the Royal Society A, 365, 303-315.
- Farrar, C.R.;Worden, K. (2012). *Structural Health Monitoring: A Machine Learning Perspective.* Wiley: Hoboken, NJ, USA.
- Finotti, R.P.; Cury, A.A.; Barbosa, F.D.S. (2019). 'An SHM approach using machine learning and statistical indicators extracted from raw dynamic measurements.' *Lat. Am. J. Solids Struct*., 16, 1–17.
- Flah, M., et al. (2020). 'Machine Learning Algorithms in Civil Structural Health Monitoring: A Systematic Review.' *Archives of Computational Methods in Engineering.*
- Geng, X. et al. (2018). 'Research on FBG-Based CFRP Structural Damage Identification Using BP Neural Network.' *Photon-Sensors,* 8, 168–175.
- Gomez-Cabrera, A. & Escamilla-Ambrosio, P.J. (2022). 'Review of Machine-Learning Techniques Applied to Structural Health Monitoring Systems for Building and Bridge Structures.' *Applied Sciences*.
- Jin, C. et al. (2016). 'Damage detection of a highway bridge under severe temperature changes using extended Kalman filter trained neural network.' *J. Civ. Struct. Health Monit.,* 6, 545–560.
- Mardiyono, M.; Suryanita, R.; Adnan, A. (2012). 'Intelligent Monitoring System on Prediction of Building Damage Index using Neural- Network.' *TELKOMNIKA (Telecommun. Comput. Electron. Control.),* 10, 155–164.
- Masood, R., Kharal, M.K.N. & Nasir, A.R. (2014). 'Is BIM Adoption Advantageous for Construction Industry of Pakistan?' *Procedia Engineering*.
- Min, J. et al. (2012). ‚Impedance-based structural health monitoring incorporating neural network technique for identification of damage type and severity.' *Eng. Struct.,* 39, 210–220.
- Montgomery, D. C. (1997). *Introduction to statistical quality control.* New York, NY: John Wiley & Sons Inc.
- Morfidis, K.; Kostinakis, K. (2017). 'Seismic parameters' combinations for the optimum prediction of the damage state of R/C buildings using neural networks.' *Adv. Eng. Softw.,* 106, 1–16.

- Mousavi, A.A. et al. (2020). ‘Structural Damage Localization and Quantification Based on a CEEMDAN Hilbert Transform Neural Network Approach: A Model Steel Truss Bridge Case Study.’ *Sensors*, 20, 1271.
- Padil, K.H. et al. (2020). ‘Non-probabilistic method to consider uncertainties in frequency response function for vibration-based damage detection using Artificial Neural Network.’ *J. Sound Vib*., 467, 115069.
- Padil, K.H.; Bakhary, N.; Hao, H. (2017). ‘The use of a non-probabilistic artificial neural network to consider uncertainties in vibration based- damage detection.’ *Mech. Syst. Signal Process.*, 83, 194–209.
- Rytter, A. (1993). *Vibrational Based Inspection of Civil Engineering Structures*. Ph.D. Thesis, Aalborg University, Aalborg, Denmark.
- Saif Ur Rehman, Toor, M., Hussaini, Q., Abdul Rafay (2022). *Development of a low-cost solution for remote Structural Health Monitoring.* NICE, SCEE, NUST.
- Sandhu, T., Ali, A., Mashood, Ali, J. (2018) *System identification of a pedestrian bridge for structural health monitoring.* NICE, SCEE, NUST.
- Shull, P. (2002*) Nondestructive Evaluation*. 1st edn. CRC Press.
- Smarsly, K.; Dragos, K.; Wiggenbrock, J. (2016). ‘Machine learning techniques for structural health monitoring.’ *In Proceedings of the 8th European Workshop on Structural Health Monitoring (EWSHM 2016)*, Bilbao, Spain, 5–8 July 2016; pp. 5–8.
- Sony, S.; Gamage, S.; Sadhu, A.; Samarabandu, J. (2022). ‘Multiclass Damage Identification in a Full-Scale Bridge Using Optimally Tuned One-Dimensional Convolutional Neural Network.’ *J. Comput. Civ. Eng*., 36, 04021035.
- Tan, Z.X.; Thambiratnam, D.P.; Chan, T.H.T.; Gordan, M.; Razak, H.A. (2019). ‘Damage detection in steel-concrete composite bridge using vibration characteristics and artificial neural network.’ *Struct. Infrastruct. Eng*., 16, 1247–1261.
- Theiler, M., Dragos, K. and Smarsly, K. (2017). ‘BIM-based design of structural health monitoring systems.’ *In Proceedings of the 11th International Workshop on Structural Health Monitoring*, Stanford, CA, USA (Vol. 12).
- Tuchkevich, E., Rechinsky, A., Vysotskiy, A., Zolotova, J. & Tuchkevich, V. (2015). ‘ADN and AP Programs for Civil Engineering Students.’ *Procedia Engineering*.
- Valinejadshoubi, M., Bagchi, A. and Moselhi, O. (2016). ‘Managing structural health monitoring data using building information modeling.’ *In Proceedings of the 2nd*

World Congress and Exhibition on Construction and Steel Structure, Las Vegas, NV, USA (pp. 22-24).

- Valinejadshoubi, M., Bagchi, A. and Moselhi, O. (2019). 'Development of a BIM-based data management system for structural health monitoring with application to modular buildings: Case study.' *Journal of Computing in Civil Engineering*, 33(3), p.05019003
- Worden, K. & Dulieu-Barton, Janice. (2004). 'An Overview of Intelligent Fault Detection in Systems and Structures.' *Structural Health Monitoring-an International Journal - STRUCT HEALTH MONIT*. 3. 85-98. 10.1177/1475921704041866.
- Zhang, R.; Liu, Y.; Sun, H. (2020). 'Physics-guided convolutional neural network (PhyCNN) for data-driven seismic response modeling.' *Eng. Struct.* 215, 110704.