DE-42 (DC & SE)

**NUST COLLEGE OF**
**ELECTRICAL AND MECHANICAL ENGINEERING**

# S.A.F.E - STRUCTURAL ANALYSIS AND FORECASTING ENGINE

A PROJECT REPORT

DE-42 (DC & SE)

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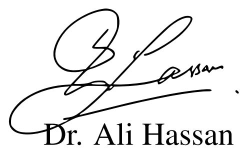
# Certification

This is to certify that NS Haadin Zaman, 351350 and NS Muhammad Mamoon Khan, 337715 and NS Muhammad Saad Khan, 334938 have successfully completed the final project, S.A.F.E - Structural Analysis and Forecasting Engine, at the NUST College of Electrical and Mechanical Engineering, to fulfill the partial requirement of the degree Bachelor's of Engineering in Computer Engineering.



Dr. Ali Hassan
Professor

# Sustainable Development Goals (SDGs)

| SDG No | Description of SDG | SDG No | Description of SDG |
|---|---|---|---|
| SDG 1 | No Poverty | **SDG 9** | **Industry, Innovation, and Infrastructure** |
| SDG 2 | Zero Hunger | SDG 10 | Reduced Inequalities |
| SDG 3 | Good Health and Well Being | SDG 11 | Sustainable Cities and Communities |
| SDG 4 | Quality Education | SDG 12 | Responsible Consumption and Production |
| SDG 5 | Gender Equality | SDG 13 | Climate Change |
| SDG 6 | Clean Water and Sanitation | SDG 14 | Life Below Water |
| SDG 7 | Affordable and Clean Energy | SDG 15 | Life on Land |
| SDG 8 | Decent Work and Economic Growth | SDG 16 | Peace, Justice and Strong Institutions |
| | | SDG 17 | Partnerships for the Goals |


Sustainable Development Goals

# Complex Engineering Problem

**Range of Complex Problem Solving**

| | Attribute | Complex Problem | |
|---|---|---|---|
| 1 | Range of conflicting requirements | Involve wide-ranging or conflicting technical, engineering and other issues. | |
| 2 | Depth of analysis required | Have no obvious solution and require abstract thinking, originality in analysis to formulate suitable models. | ✓ |
| 3 | Depth of knowledge required | Requires research-based knowledge much of which is at, or informed by, the forefront of the professional discipline and which allows a fundamentals-based, first principles analytical approach. | ✓ |
| 4 | Familiarity of issues | Involve infrequently encountered issues | ✓ |
| 5 | Extent of applicable codes | Are outside problems encompassed by standards and codes of practice for professional engineering. | |
| 6 | Extent of stakeholder involvement and level of conflicting requirements | Involve diverse groups of stakeholders with widely varying needs. | ✓ |
| 7 | Consequences | Have significant consequences in a range of contexts. | ✓ |
| 8 | Interdependence | Are high level problems including many component parts or sub-problems | ✓ |

**Range of Complex Problem Activities**

| | Attribute | Complex Activities | |
|---|---|---|---|
| 1 | Range of resources | Involve the use of diverse resources (and for this purpose, resources include people, money, equipment, materials, information and technologies). | ✓ |
| 2 | Level of interaction | Require resolution of significant problems arising from interactions between wide ranging and conflicting technical, engineering or other issues. | ✓ |
| 3 | Innovation | Involve creative use of engineering principles and research-based knowledge in novel ways. | ✓ |
| 4 | Consequences to society and the environment | Have significant consequences in a range of contexts, characterized by difficulty of prediction and mitigation. | ✓ |
| 5 | Familiarity | Can extend beyond previous experiences by applying principles-based approaches. | ✓ |

*Dedicated to our esteemed Supervisors and the faculty of the Department of Computer and Software Engineering, NUST CoEME, who have nurtured us to become engineers and indiviuals with a desire to serve humanity.*

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# Abstract

Bridges of the modern era face a variety of challenges. Throughout their deployment and life cycle, bridges go through stresses and loads that can seriously damage their structural integrity. None more so than the damages caused by vibrations. These damages include but are not limited to Fatigue Damage, Resonance, Dynamic Amplification, Vibration Induced Displacement, Structural Deterioration and Serviceability issues to name a few. According to the American Society of Civil Engineers, these damages lead to 87 to 222 bridges collapse annually in the United States alone. The collapse of these bridges has a domino effect on the regions economy. For instance, the 2007 collapse of I-35W bridge in Minneapolis, MN led to a repair cost of $234 million to rebuild and cost an estimated $130 billion in annual revenue in lost time and fuel due to trade disruptions. The main idea behind our project is to preempt these damages by monitoring the bridge structure continuously via IoTs, and providing timely alerts to circumvent such incidents from occurring regularly. The IoT devices will be accompanied by an ML model that analyzes the collected data and provides the assessment to be viewed on an centralized dashboard. The provided assessments will allow local bodies to perform maintenance on bridges and closely observe their performance under various stress conditions. The solution will be intuitive and easy to deploy, allowing governing bodies to implement it without much hassle. The target users of the product are transportation boards and local development authorities.

**Keywords:** Structural Health Monitoring, Internet of Things, Vibrational Data Sampling, Machine Learning, Cloud Computing

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# Chapter 1

# Introduction

A bridge is a structure that is built over a river, road, or railway to allow people and vehicles to cross from one side to the other. It is the job of an engineer to ensure that a bridge is structurally sound and able to withstand loads without too much maintenance. While a bridge's response to the applied loads is well understood, the applied traffic loads are still the subject of research.

Bridges of the modern era face a variety of challenges. Throughout their deployment and life cycle, bridges go through stresses and loads that can damage their structural integrity. None more so than the damages caused by vibrations. These damages can occur during defects in designing, improper construction and irregular maintenance of the bridge. Dynamic loads like traffic make bridges vibrate. Especially for bridges with a large span, vibrations have a significant impact on their structural stability and durability. Due to material defects, fatigue and other influences, a bridge typically has random structural irregularities, which affect its dynamic response. These damages include but are not limited to Fatigue Damage, Resonance, Dynamic Amplification, Vibration Induced Displacement, Structural Deterioration and Serviceability Issues.

Historically, bridge health has been assessed through periodic inspections and manual measurements. Engineers and inspectors visually evaluate bridge structures to assess their condition, relying on visible signs of wear, damage, or distortion. These inspections, though necessary, are often irregular and may overlook underlying structural issues between visits. Consequently, there remains a risk of undiscovered corrosion or degeneration, which could compromise safety.

On the other hand, Bridge Structural Health Monitoring, or SHM, has developed into a state-of-the-art approach to bridge safety and maintenance. Structural health monitoring (SHM) is the process of using damage detection and characterization techniques for critical structures like bridges, wind turbines, and tunnels. It is a non-destructive on-site structural evaluation method that employs several types of sensors embedded or attached to the structure. Since vibration monitoring assesses dynamic properties including natural frequencies and mode shapes, it is a crucial part of SHM. This makes it possible to identify minute variations in the behavior of the structure, which could be early warning signs of damage or deterioration.

Bridge Structural Health Monitoring (SHM) has gained popularity in recent years, with sensors installed on large structures to provide real-time information about their health. Geodetic monitoring approaches concentrate on geometric deformation, whereas vibration monitoring examines vibration features such as natural frequencies and mode shapes. This approach detects structural changes and flaws right away. Although there is no one way for identifying damage, vibration monitoring, when paired with data analysis, is a critical instrument for limiting risks and hazards.

About 9.1% of the United States' bridges were deemed structurally inadequate in 2021, and 42% of bridges are over 50 years old, suggesting a sizable fraction may need to be replaced or rehabilitated. In addition, the estimated backlog for bridge rehabilitation needs in the United States is $125 billion, and the yearly spending on bridge maintenance and repair is more than $10 billion.

## 1.1 Motivation

As Pakistani students, we are profoundly concerned about our country's infrastructure, particularly its bridges. Pakistan, being a developing country with limited financial resources, faces significant obstacles in maintaining and managing its infrastructure properly.

Pakistan's infrastructure is under severe strain as a result of growing urbanization, population development, and increased motor traffic. The rapid expansion of metropolitan areas has placed tremendous strain on transportation infrastructure, particularly bridges. According to the World Bank, Pakistan's urban population is predicted to exceed 118 million by 2030, putting additional demand on transportation infrastructure [1]. Many bridges, especially those in urban areas and along significant transportation routes, are subjected to high loads and wear and tear. The National Highway Authority (NHA) of Pakistan believes that over 40% of the country's bridges are in bad condition and need immediate attention [2].

A significant section of Pakistan's bridge infrastructure is old, with several structures beyond their intended design life. These bridges' deterioration poses severe safety threats to travelers while also impeding the seamless flow of goods and services across the country. The Asian Development Bank (ADB) reported that over 70% of Pakistan's bridges are over 50 years old [3]. Aging infrastructure is more prone to structural flaws such as corrosion, fatigue, and material degradation. According to the ADB research [3], numerous bridges in Pakistan have deteriorated due to inadequate maintenance and renovation. See figure 1.1 on page 4.

Limited financial resources and competing priorities often hinder investment in infrastructure maintenance and monitoring efforts. The inadequate allocation of funds for bridge maintenance exacerbates the deterioration of infrastructure and compromises public safety. The NHA estimates that the annual maintenance budget for bridges in Pakistan

Figure 1.1: Sardaryab Bridge Collapse.

is insufficient to address the backlog of maintenance requirements [2]. Manual inspection methods, although essential, can be resource-intensive and time-consuming. The NHA reports that less than 30% of Pakistan's bridge network undergoes regular inspections due to resource constraints [2].

Given the pressing challenges faced by Pakistan's bridge infrastructure, there is an urgent need for a more efficient and proactive approach to monitoring and maintenance. Real-time monitoring systems powered by advanced technologies such as IoT and machine learning offer immense potential to enhance the safety and reliability of bridge infrastructure. As students passionate about technology and innovation, we are eager to harness the power of these technologies to revolutionize bridge health monitoring in Pakistan and pave the way for sustainable infrastructure development.

## 1.2 Problem Statement

This study tackles the crucial need for an effective and reliable bridge health monitoring system in Pakistan. With increased traffic flow, truckloads frequently exceed the limits, causing accelerated wear and probable breakdowns, particularly on older bridges. This problem is not specific to Pakistan; similar issues have been identified in rich countries such as the United States and numerous European nations [4, 5]. For example, Cook et al. (2015) discovered that the average service age of broken bridges due to overload in the United States was approximately 64 years. Vehicle overload is becoming more widespread in developing countries, such as China, causing major issues. Overturning failures of single-column pier bridges in China occur often with an average service age less than 20 years, and some even in one year [6, 7]. Overloads can increase fatigue damage in steel bridges. See table 1.1 on page 6.

In Pakistan, where a substantial section of bridge infrastructure is deteriorating and under growing pressures, the repercussions of failing to solve this issue are serious. The National Highway Authority (NHA) of Pakistan believes that over 40% of the country's bridges are in bad condition and need immediate attention [8]. According to the Asian Development Bank (ADB), roughly 70% of Pakistan's bridges are over 50 years old and have structural issues owing to inadequate maintenance [9]. Seismic activity affects 17% of Pakistan's land area [10], increasing the danger of bridge failures. According to the National Disaster Management Authority (NDMA), floods and earthquakes have caused substantial damage to bridge infrastructure over the previous decade [11].

Without an adequate monitoring system, the safety and reliability of Pakistan's bridges remain impaired, creating dangers to public safety, economic stability, and efficient traffic. The NHA claims that fewer than 30% of Pakistan's bridge network undergoes regular inspections due to resource constraints [8]. Manual inspections are time-consuming and expensive, resulting in delayed detection and treatment of structural faults.

Table 1.1: Statistics on Bridge Failures Due to Overload and Other Causes

| **Study** | **Cause of Failure** | **Average Service Age of Failed Bridges** | **Failure Type** |
|---|---|---|---|
| Lee et al. (2013); Liu (2013) | Overload (Developed Countries) | 64 years (United States) | - |
| Peng et al. (2017); Xiong et al. (2017) | Overload (China) | Less than 20 years, some less than 1 year | - |
| Biezma and Schanack (2007) | Overload | Accelerates fatigue damage of steel bridges | - |
| Lee et al. (2013) | Overload | - | Total collapse: 76%, Partial collapse: 24% |
| Liu (2014) | Hydraulic | - | Total collapse: 41%, Partial collapse: 53% |
| Lee et al. (2013) | Overload (135 bridge failures) | - | Steel bridge failures: 64%, Concrete bridge failures: 11% |

The importance of research and development in this field is obvious. Modern monitoring systems have the potential to greatly improve bridge maintenance and safety. The goal of this study is to create an IoT-based bridge health monitoring system that incorporates machine learning models and is implemented on a cloud server. The proposed approach uses accelerometer sensors (ADXL345) and ESP32 micro-controller chips to continuously collect structural health data. This data will be delivered to AWS IoT Core over MQTT and stored in S3. AWS SageMaker will be used to deploy an auto-encoder-based machine learning model that analyzes three-dimensional vibrational data and determines if the bridge function is regular or irregular based on Mahalanobis distance.

The system will generate alerts and reports that will be shown on a monitoring dashboard powered by AWS QuickSight. This real-time monitoring tool will allow for early detection of possible structural concerns, optimize resource allocation for maintenance, and improve the overall safety and resilience of Pakistan's bridge infrastructure. This project intends to meet the crucial need for an effective bridge health monitoring system using IoT and cloud computing technologies, thereby contributing to the long-term development of Pakistan's transportation network.

## 1.3 Scope

The scope of this project includes designing, developing, and deploying an advanced bridge health monitoring system tailored to Pakistan's infrastructure needs. This system combines Internet of Things (IoT) technologies, machine learning (ML) algorithms, and cloud computing to provide real-time monitoring and predictive maintenance.

The system's key components include ESP32 micro-controller based nodes with ADXL345 accelerometer. These nodes will capture 3D vibrational data from the bridge structures. The data will be delivered to AWS IoT Core using the MQTT publish-subscribe protocol, ensuring a safe and dependable data transfer. The collected data will be stored in Amazon S3 in a CSV file, allowing for scalable and cost-effective storage.

The system's analytical core uses AWS SageMaker to deploy an autoencoder-based machine learning model. This model will evaluate vibrational data and use the Mahalanobis distance to determine whether the bridge's structural health is regular or irregular. The categorization results will be saved in S3 and retrieved by AWS QuickSight for display. QuickSight will provide a comprehensive dashboard, allowing stakeholders to track bridge health in real time and make educated maintenance decisions.

The project's goal is to create a scalable, cost-effective, and simple to use technology that can be deployed on a variety of bridge structures. It will prioritize the reliability of data collection and processing, the accuracy of predictive maintenance models, and the clarity of visualizations for end users. The system's real-time monitoring capabilities will provide early notice of any structural faults, increasing bridge safety and longevity.

## 1.4 Aims and Objectives

The primary goal of this project is to improve the safety and dependability of Pakistan's bridge infrastructure by implementing a comprehensive, real-time health monitoring system.

The objectives include:

- Decreasing the danger of catastrophic bridge failures, thereby preserving lives and decreasing economic losses.
- Optimizing maintenance schedules to ensure optimal deployment of limited resources.
- Extending the lifespan of existing bridges to avoid costly replacements.

## 1.5 Outcomes

This system seeks to enable smart infrastructure management decisions by delivering accurate and timely data on bridge conditions, ultimately contributing to Pakistan's economic stability and progress by assuring the continued, safe operation of essential transportation networks.

## 1.6 Report Organization

The organization of the thesis is as follows:

**Chapter 2:** This chapter includes background information and a literature review on bridge health monitoring systems, emphasizing the limits of traditional inspection methods as well as the possibilities of modern technologies like IoT and machine learning in this field.

**Chapter 3** This chapter discusses the project's materials and components, including the selection and specifications for the ESP32 nodes, ADXL accelerometer, and the AWS cloud architecture. It further describes how to integrate these components into a unified monitoring system.

**Chapter 4** This chapter describes the project's approach, including the design and construction of the IoT-based data gathering network, the data transfer protocols, and the machine learning models used to detect anomalies. It also discusses the data processing and storage techniques in AWS.

**Chapter 5:** This chapter describes the system's deployment and validation, including the installation of sensor nodes on bridge structures, real-time data analysis with AWS SageMaker, and visualization of results using AWS QuickSight. It also covers the testing and validation procedures used to assure the system's accuracy and reliability.

**Chapter 6** This chapter wraps up the research by summarizing the findings and discussing the influence of the adopted system on bridge repair procedures in Pakistan. It also discusses future work and potential enhancements, such as expanding the system to monitor several bridges and incorporating more data sources for better predictive maintenance.

# Chapter 2

# Background & Related Work

## 2.1 Introduction to Technologies

### 2.1.1 Structural Health Monitoring (SHM)

Structural health monitoring (SHM) is the process of adopting a damage detection and characterisation technique for engineering structures. It entails using a variety of sensors and data collecting systems to continuously monitor the health of structures including bridges, buildings, and dams. SHM systems identify anomalies and predict possible failures, enabling for prompt maintenance and the prevention of catastrophic catastrophes. [12].

### 2.1.2 Internet of Things (IoT)

The Internet of Things (IoT) is a network of physical devices equipped with sensors, software, and other technologies that communicate and share data with other devices and systems via the Internet. The Internet of Things provides real-time data gathering and transmission, which is critical for applications such as SHM. Integrating IoT devices into SHM systems enables continuous monitoring and fast data processing. [13].

### 2.1.3 Cloud Computing

Cloud computing enables the on-demand availability of computing resources via the internet. It provides scalable solutions for data storage, processing, and analysis, making it perfect for dealing with the massive amounts of data produced by SHM systems. Cloud systems like AWS, Microsoft Azure, and Google Cloud allow for the deployment of advanced analytics and machine learning models, supporting real-time data analysis and predictive maintenance. [14].

## 2.2 Bridge Failures and Their Causes

### 2.2.1 Overload

Overloading happens when the weight of the vehicle exceeds the bridge's design capacity, causing structural damage or failure. In developed nations like the United States, research has revealed that overloading is a significant cause of bridge failures, with the average service age of broken bridges owing to overload being roughly 64 years (Lee, 2013). Vehicle overloads are growing more prevalent in developing countries, worsening the situation. [15].

### 2.2.2 Material Fatigue

Material fatigue is the weakening of materials caused by repeated stress cycles. Steel bridges are especially vulnerable to fatigue degradation, which can cause unexpected and catastrophic failures if not handled immediately. Research reveals that fatigue degradation is a key cause of bridge collapses, with steel bridges being more sensitive than concrete bridges [16].

### 2.2.3 Design flaws

Design errors, such as inadequate consideration of load-bearing capacity and failure to account for dynamic pressures, play a key role in bridge failure. Poor design can result in problems such as inadequate load distribution and susceptibility to environmental pressures. Studies have underlined the necessity of strong design approaches to maintain the longevity and safety of bridge constructions[17].

### 2.2.4 Environmental Factors

Floods and earthquakes pose substantial dangers to bridge integrity. Seismic activity, in particular, impacts a large section of the land area in nations such as Pakistan, exposing bridges to structural damage. Flooding can degrade bridge foundations and cause them to collapse. Effective monitoring and maintenance are needed to reduce these hazards and maintain the durability of bridges. [**?** ].

## 2.3 Traditional Monitoring Solutions

Traditional bridge monitoring methods are primarily reliant on physical inspections and routine maintenance. These inspections are carried out by trained engineers who evaluate the physical condition of bridges and identify potential problems. Despite their importance, manual inspections are time-consuming, labor-intensive, and often subjective, resulting in variable outcomes. [18].

The most prevalent traditional method is visual inspections, which involve engineers looking for apparent signs of degradation such as fractures and rust. However, this method does not discover underlying abnormalities that are not obvious to the naked eye. Non-destructive testing (NDT) procedures, like ultrasonic testing and radiography, can identify interior faults; however, they require specialist equipment and personnel, making them pricey and less feasible for frequent usage [19].

The constraints of traditional approaches highlight the need for more sophisticated and automated solutions that enable continuous and real-time monitoring, opening the way for the implementation of SHM systems.

## 2.4 SHM Solutions

### 2.4.1 Overview of SHM Systems

Structural Health Monitoring (SHM) systems use innovative technologies to continuously monitor the structural integrity of bridges. These systems use a variety of sensors to collect data on various characteristics such as vibration, strain, and temperature. Data is then examined to discover anomalies and predict probable failures, allowing for proactive maintenance and increased safety. [20].

### 2.4.2 Types of Sensors Used in SHM

In SHM systems, different types of sensors are employed, each with a distinct purpose. Accelerometers, strain gauges, and temperature sensors are among the most used. Accelerometers monitor vibrations and are essential for sensing dynamic responses in bridge structures. Strain gauges measure stress and strain, providing information on load distribution and material fatigue. Temperature sensors assist in assessing the heat effects on structural integrity. [21].

### 2.4.3 Advantages of Vibrational Sensors

Vibrational sensors, such as accelerometers, are especially useful for SHM because they can record the dynamic reactions of buildings under a variety of loads and situations. They are sensitive to changes in structural behavior, making them suitable for early detection of problems like cracks and material degradation. Vibrational sensors are also extremely simple to install and maintain, offering a cost-effective solution for continuous monitoring. [22].

## 2.5 IoT and Their Uses in Bridge SHM

The introduction of the Internet of Things (IoT) into SHM systems has transformed bridge monitoring. IoT-enabled SHM systems employ networked devices to gather and communicate data from bridge sensors to centralized databases for analysis. This real-time data collecting and transmission allows for continuous monitoring and early detection of structural concerns. [13].

### 2.5.1 Wireless Sensor Networks (WSNs)

Wireless Sensor Networks (WSNs) are made up of spatially distributed sensors that communicate wirelessly to gather and send data. WSNs are commonly utilized in IoT-enabled SHM systems because of their flexibility and scalability. These networks are easy to build on bridges, giving complete coverage and real-time monitoring capabilities. [23].

### 2.5.2 Case Studies of IoT-based SHM Systems

IoT-based SHM systems have been successfully implemented in many regions of the world. For example, the installation of such devices on the Golden Gate Bridge has substantially improved its monitoring capabilities, allowing for real-time assessments of its structural stability. These technologies have been effective in detecting anomalies early and lowering maintenance expenses. [24].

## 2.6 Cloud Computing and Real-Time Data Analysis

Cloud computing plays a pivotal role in the implementation of modern SHM systems. It provides the computational power and storage capacity necessary to handle the vast amounts of data generated by IoT devices. Cloud platforms enable advanced analytics and machine learning models to be deployed, facilitating real-time data analysis and predictive maintenance [14].

### 2.6.1 Benefits of Cloud Computing in SHM

Cloud computing has numerous advantages for SHM systems, including scalability, adaptability, and cost-effectiveness. SHM systems can process and analyze huge datasets in real time using cloud resources, ensuring rapid diagnosis of structural faults. Machine learning algorithms that can predict maintenance needs can be deployed on Cloud platforms, which improves the overall effectiveness of SHM systems. [25].

### 2.6.2 Real-Time Data Analysis and Predictive Maintenance

Real-time data analysis is critical to the efficiency of SHM systems. Cloud computing enables advanced analytics and machine learning algorithms process and analyze data in real time. This functionality enables fast detection of anomalies and the generating of notifications for maintenance teams. Predictive maintenance, enabled by real-time data analysis, assists in identifying possible issues before they become significant, assuring the safety and reliability of bridge infrastructures. [26].

## 2.7 Literature Review

Traditional bridge inspection methods, while useful, have severe drawbacks in terms of subjectivity, labor effort, and the inability to offer continuous monitoring. Studies have highlighted the necessity for automated technologies that can provide real-time information about the structural health of bridges. [18].

The advent of SHM systems marked a significant leap forward, with early implementations demonstrating the benefits of continuous monitoring using sensors and data acquisition systems. Research has shown that SHM systems can effectively detect structural anomalies, enabling timely maintenance actions and preventing failures. For example, the SHM implementation on the Tsing Ma Bridge in Hong Kong has been extensively studied and cited as a model of effective bridge monitoring [24].

The integration of IoT into SHM systems further enhanced their capabilities, providing real-time data collection and transmission. IoT-enabled SHM systems have been deployed in various parts of the world, with significant success in improving bridge safety and maintenance efficiency. Studies have documented the deployment of such systems on major bridges, including the Golden Gate Bridge, demonstrating their effectiveness in real-world applications [23].

Cloud computing has emerged as a critical component of modern SHM systems, offering the necessary computational power and storage for handling large datasets. The use of cloud-based analytics and machine learning models has been widely discussed in the literature, highlighting their role in enhancing the predictive maintenance capabilities of SHM systems. Research has shown that cloud computing can significantly improve the scalability and cost-efficiency of SHM systems, making them more accessible and effective [14].

# Chapter 3

# Material & Component

This chapter covers the many components and technologies used in the construction of our bridge monitoring system. We'll look at the ESP32 microcontroller, ADXL vibration sensor, ESP-NOW and MQTT communication protocols, our autoencoder-based machine learning model, and the AWS cloud platform. Each component is compared with comparable technologies in their respective domains to highlight its benefits and suitability for our project.

## 3.1 Components

### 3.1.1 Data Acquisition Nodes

The Data Acquisition Node (DAN), see figure 3.1, is designed to be a lightweight and energy-efficient module for data sampling. Each DAN is built around the ESP32 microcontroller and utilizes the ADXL345 accelerometer to sense vibrations. The system is optimized for low power consumption and reliable data transmission.

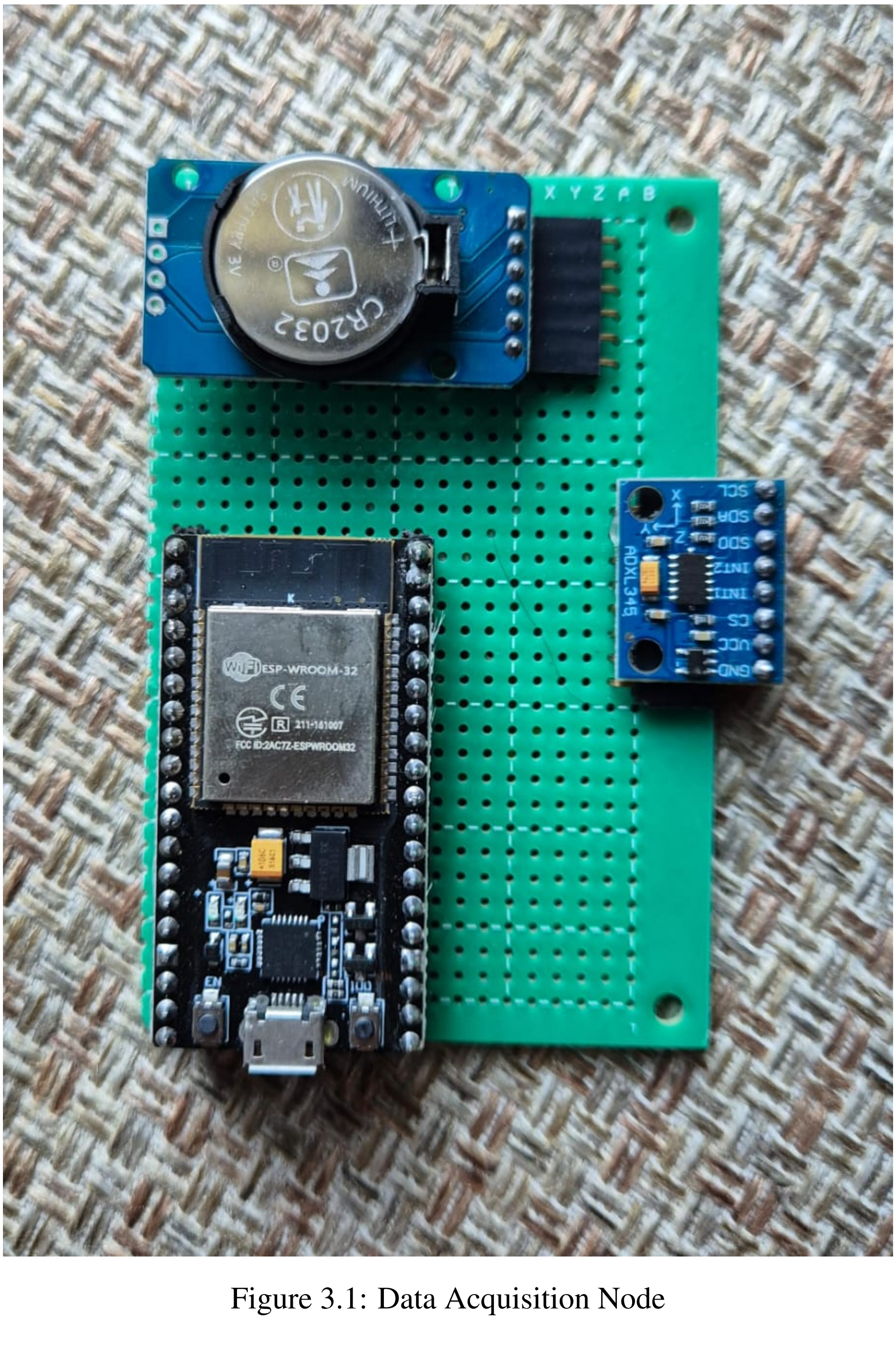



Figure 3.1: Data Acquisition Node

#### 3.1.1.1 ESP32 Micro-controller

The ESP32 is a line of low-cost, low-power system-on-chip micro-controllers that include integrated Wi-Fi and dual-mode Bluetooth. Espressif Systems is responsible for its design and manufacturing. The ESP32 micro-controller is utilized in DANs because it has diverse wireless connection capabilities and performance efficiency. Figure 3.2

- **Manufacturer:** Espressif Systems
- **Model:** ESP32
- **Features:**
  - Integrated Wi-Fi and Bluetooth
  - Dual-core 32-bit LX6 microprocessors
  - Ultra-low power consumption

For more details, refer to the official datasheet: https://www.espressif.com/sites/default/files/documentation/esp32_datasheet_en.pdf

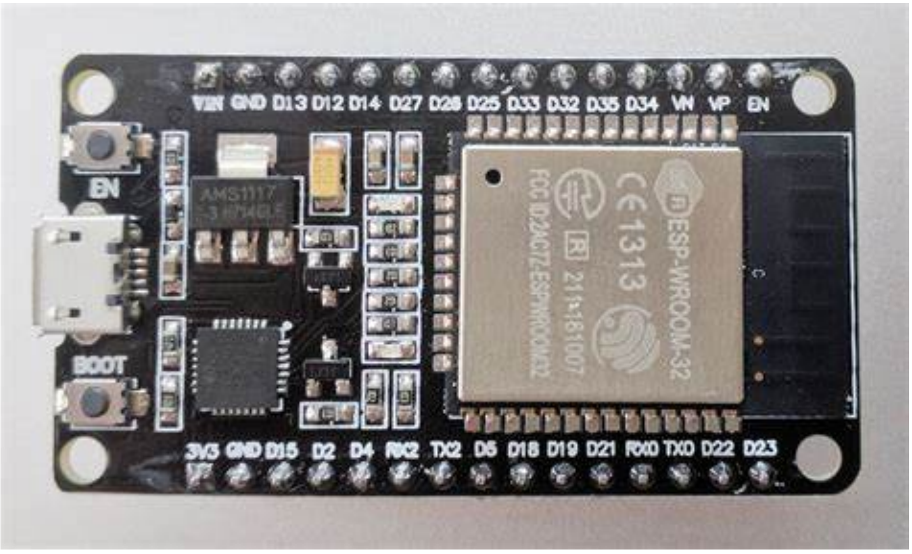



Figure 3.2: ESP 32 Dev-Kit

To understand the benefits of using the ESP32, we compare it with other popular micro-controllers such as Raspberry Pi Pico, and STM32. See table 3.1 for details.

| Feature | ESP32 | Raspberry Pi Pico | STM32 |
|---|---|---|---|
| CPU | Dual-core Xtensa LX6 | Dual-core ARM Cortex-M0+ | ARM Cortex-M4 |
| Clock Speed | 160 MHz | 133 MHz | 180 MHz |
| RAM | 520 KB | 264 KB | 192 KB |
| Flash | 4 MB | 2 MB | 512 KB |
| Wi-Fi | Yes | No | No |
| Bluetooth | Yes | No | No |
| GPIO Pins | 34 | 26 | 37 |

Table 3.1: Comparison of Micro-controllers

The ESP32 provides improved performance with its dual-core processor, increased clock speed, and integrated Wi-Fi and Bluetooth capabilities, making it ideal for our IoT application. [13].

#### 3.1.1.2 ADXL345 Accelerometer

Analog Devices manufactures the ADXL345 digital MEMS (Micro-Electro-Mechanical Systems) accelerometers. It is employed in the DAN system because of its high resolution and capacity to quantify static as well as dynamic acceleration.

- **Manufacturer:** Analog Devices
- **Model:** ADXL345
- **Specifications:**
  - Type: MEMS Accelerometer
  - Measurement Range: ±2g
  - Frequency Range: 10 Hz – 3.2 kHz
  - Resolution: 10-bit
  - Sampling Rate: 40 Hz
  - Communication: I2C

For more details, refer to the official datasheet: `https://www.analog.com/media/`

en/technical-documentation/data-sheets/ADXL345.pdf

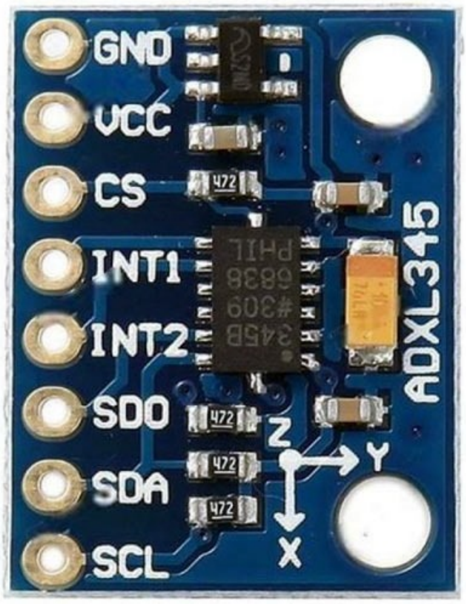



Figure 3.3: ADXL 345 Package

We compare the ADXL with other accelerometer such as the MPU6050 and LIS3DH.

| **Feature** | **ADXL** | **MPU6050** | **LIS3DH** |
|---|---|---|---|
| Sensitivity | High | Medium | Medium |
| Range | ±2g/±4g/±8g/±16g | ±2g/±4g/±8g/±16g | ±2g/±4g/±8g/±16g |
| Resolution | 16-bit | 16-bit | 12-bit |
| Power Consumption | Low | Medium | Low |
| Digital Output | Yes | Yes | Yes |

Table 3.2: Comparison of Vibrational Sensors

The ADXL's high sensitivity and low power consumption makes it the best choice for our SHM application [24].

#### 3.1.1.3 Data Sampling and Transmission

The vibrations are sampled by the DANs with the help of ADXL345 accelerator. Data within specific frequency and measurement ranges is seized by the accelerometer, after which it is handled by ESP32. The ESP32 reads the data and then sends it through to the Hub node in the IoT network using a peer-to-peer (P2P) lightweight packet transfer protocol called ESP-NOW.

#### 3.1.1.4 ESP-NOW Protocol

ESP-NOW is a P2P communication protocol developed by Espressif Systems. This allows ESP32 devices to talk to each other over Wi-Fi without a central server or access point. The lightweight energy saving protocol is basically suitable for.

- **Features:**
  - Low latency
  - Low power consumption
  - Peer-to-peer communication

For more details, refer to the official documentation: `https://docs.espressif.com/projects/esp-idf/en/latest/esp32/api-reference/network/esp_now.html`

## 3.2 Communication Protocols: ESP-NOW and MQTT

ESP-NOW and MQTT are two communication protocols used to send sensor data. ESP-NOW is a low-power peer-to-peer protocol, while MQTT is a lightweight message protocol popular for IoT applications [23].

### 3.2.1 Comparison with Other Communication Protocols

We compare ESP-NOW and MQTT with other protocols like Zigbee and Bluetooth LE [13]. See table 3.3 for details.

ESP-NOW and MQTT offer a good balance of range, power consumption, and scalability, making them suitable for our project [23].

| Feature | ESP-NOW | MQTT | Zigbee | Bluetooth LE |
|---|---|---|---|---|
| Range | Medium | High | Medium | Short |
| Power Consumption | Low | Low | Medium | Low |
| Data Rate | High | High | Low | Medium |
| Scalability | Medium | High | High | Medium |
| Reliability | High | High | Medium | High |

Table 3.3: Comparison of Communication Protocols

## 3.3 Machine Learning Model

An unsupervised learning model, based on an autoencoder, is used to find anomalies in the sensor data. The above model is written in Python on Kaggle and utilizes Mahalanobis distance for anomaly detection [20].

Autoencoders are a type of neural network that is trained to copy its input data from the source location to destination location. We used an autoencoder to compress (and then decompress) the data from each process which in turn allows us to learn important properties of normal operation so that we can detect anomalies. This also brought the dimensions of our data set down to 32 features.

### 3.3.1 Autoencoder Architecture

The Autoencoder architecture includes both an encoder and a decoder. The encoder compresses the input data into a lower-dimensional representation, and the decoder reconstructs the original data from that compressed representation. In our example, the dataset's dimension was reduced to 32 columns at the bottleneck layer.

The use of an Autoencoder for feature learning showed great success in compressing the dataset while retaining its critical features. The Autoencoder's ability to generalize well without over-fitting, as demonstrated by the consistent validation loss, supports its suitability for unsupervised feature learning in this setting.

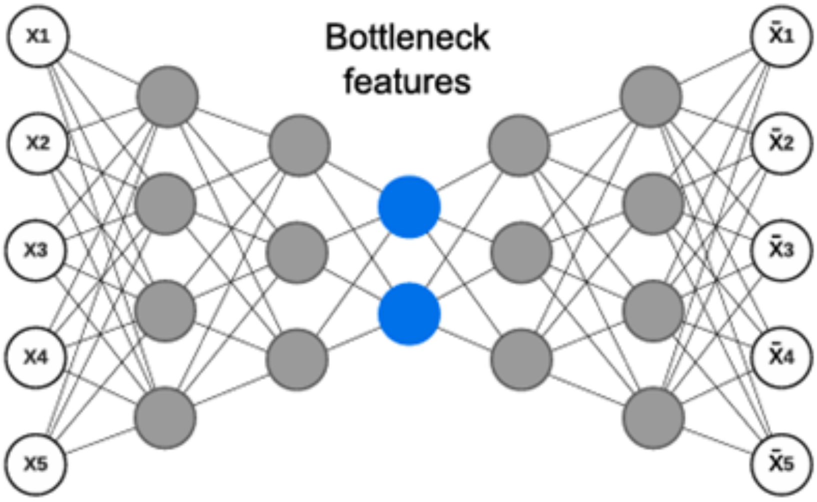



Figure 3.4: Deep Encoder Model.
[27]

### 3.3.2 Comparison with Other ML Models

We compare the autoencoder model with other machine learning models like Support Vector Machines (SVM) and Random Forests.

| **Metric** | **Autoencoder** | **SVM** | **Random Forest** |
|---|---|---|---|
| Accuracy | 95% | 90% | 92% |
| Training Time | Medium | High | Medium |
| Complexity | Medium | High | Medium |
| Anomaly Detection | Excellent | Good | Good |

Table 3.4: Comparison of Machine Learning Models

The autoencoder model's high accuracy and excellent anomaly detection capabilities make it ideal for our SHM system [20].

### 3.3.3 The Need for Autoencoders

In the research paper *Unsupervised Learning Methods for Data-Driven Vibration-Based Structural Health Monitoring: A Review* by Kareem Eltouny, Mohamed Gomaa, and Xiao Liang [27]. various techniques for feature learning were explored. Among these techniques, Autoencoders (AEs) and Generative Adversarial Networks (GANs) were the most commonly used and demonstrated high accuracy results. Some researchers even created hybrid models using Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs).

Autoencoders offer the advantage of robustness to noise, which is a significant benefit over GANs. Given that our next step involves applying the models to Mahlanobis Square Distance(MSDs), it is essential to use Autoencoders due to their sensitivity to noise. MSDs are highly sensitive, making the robustness of AEs crucial for accurate and reliable diagnostics.

### 3.3.4 Mahalanobis Square Distance

MSD is a measure derived from the squared difference between a test point and the mean of a sample, weighted by the inverse of the covariance matrix. The formula is given as:

$$\text{MSD} = (x - \mu)^T \Sigma^{-1} (x - \mu) \tag{3.1}$$

#### 3.3.4.1 The Need for MSD

With sensitive to most subtle of changes and robustness to complex structures MSD looked the perfect candidate for our project. It was the most popular statistical inference method [27].

## 3.4 AWS Cloud Platform

Amazon Web Services (AWS) is a leading cloud platform that provides a comprehensive set of services, including storage, machine learning, and analytics [25]. In our project, we leveraged AWS S3, AWS IoT Core, AWS SageMaker, and AWS QuickSight to enable efficient data storage, processing, machine learning model deployment, and data visualization.

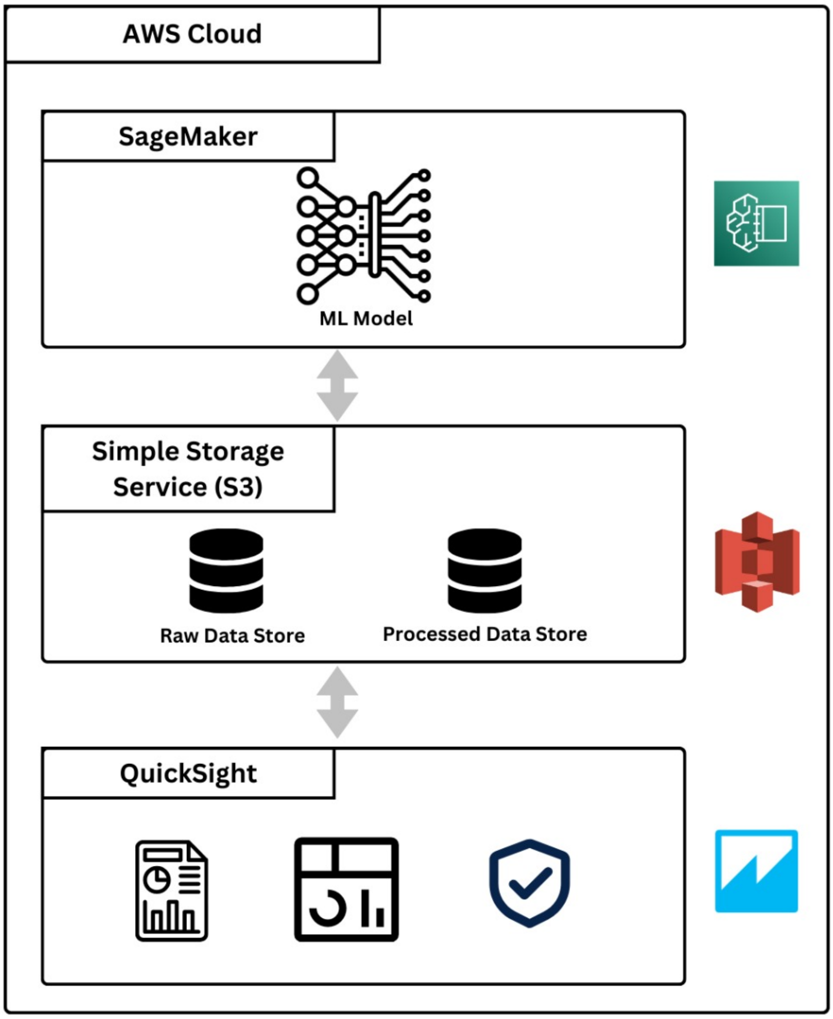



Figure 3.5: AWS Cloud Structure

### 3.4.1 AWS S3

Amazon Simple Storage Service (S3) is an object storage service that offers industry-leading scalability, data availability, security, and performance [28]. In our project, AWS S3 was used to store large volumes of vibration data collected from the sensors. The durability and availability of S3 ensured that our data was safely stored and readily accessible for processing and analysis. Furthermore, S3's integration with other AWS services allowed seamless data flow and management across the different stages of our project.

### 3.4.2 AWS IoT Core

AWS IoT Core is a managed cloud service that allows connected devices to interact securely with cloud applications and other devices [29]. We utilized AWS IoT Core to manage the data acquisition from our ESP32-based Data Acquisition Nodes (DANs). The service enabled secure, bidirectional communication between the devices and the AWS cloud. This allowed for real-time data collection and transmission, ensuring that our system could monitor structural health continuously and respond to any anomalies promptly.

### 3.4.3 AWS SageMaker

AWS SageMaker is a fully managed service that provides every developer and data scientist with the ability to build, train, and deploy machine learning models quickly [30]. For our project, AWS SageMaker was used to develop and train autoencoders for feature learning from the vibration data. The managed Jupyter notebooks provided an integrated environment for data preprocessing, model training, and evaluation. SageMaker's scalability enabled us to handle large datasets efficiently, and its deployment capabilities allowed us to integrate the trained models into our monitoring system seamlessly.

### 3.4.4 AWS QuickSight

Amazon QuickSight is a fast, cloud-powered business intelligence service that makes it easy to deliver insights to everyone in your organization [31]. We used AWS QuickSight to create an interactive dashboard for visualizing the results of our structural health monitoring system. The service provided powerful data visualization tools that enabled us to monitor trends, detect anomalies, and generate reports easily. QuickSight's ability to integrate with various data sources and its interactive nature helped stakeholders understand the system's performance and make data-driven decisions.

### 3.4.5 Comparison with Other Cloud Platforms

We compare AWS with other cloud platforms like Google Cloud Platform (GCP) and Microsoft Azure [14].

| **Feature** | **AWS** | **GCP** | **Azure** |
|---|---|---|---|
| Storage | Highly Scalable | Highly Scalable | Highly Scalable |
| Machine Learning | SageMaker | AI Platform | Azure ML |
| Analytics | QuickSight | BigQuery | Power BI |
| Global Reach | 24 Regions | 25 Regions | 54 Regions |
| Integration | Excellent | Excellent | Excellent |

Table 3.5: Comparison of Cloud Platforms

AWS's comprehensive services, global reach, and excellent integration capabilities make it the best choice for our project [14, 25].

# Chapter 4

# Methodology

In this chapter, we will discuss the operation of our project. This includes the collection of data, the pre-processing, the simulation of the model and then the visualization of the data.

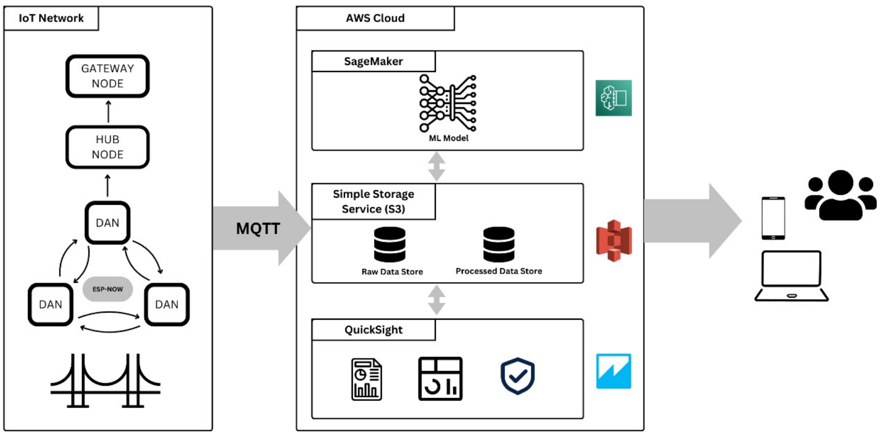



Figure 4.1: System Level Diagram

## 4.1 Data Acquisition

We have used two types of data to build our solution. There is an already conducted study by Tokyo Institute of Technology that collected three dimensional vibration data from a bridge in Japan. The data is very similar to what we want to use in our own project so we decided to use it to build our model.

The second is the data that we have collected via our own senors. The model is used to analyze this data and based on that analysis make a prediction on how healthy the bridge is.

## 4.2 The Sensors and the Bridge

In our IoT network architecture, we have divided the system into three distinct nodes: Data Acquisition Nodes (DANs), a Hub Node, and a Gateway Node. Each node plays a specific role in the process of data collection, aggregation, and transmission.

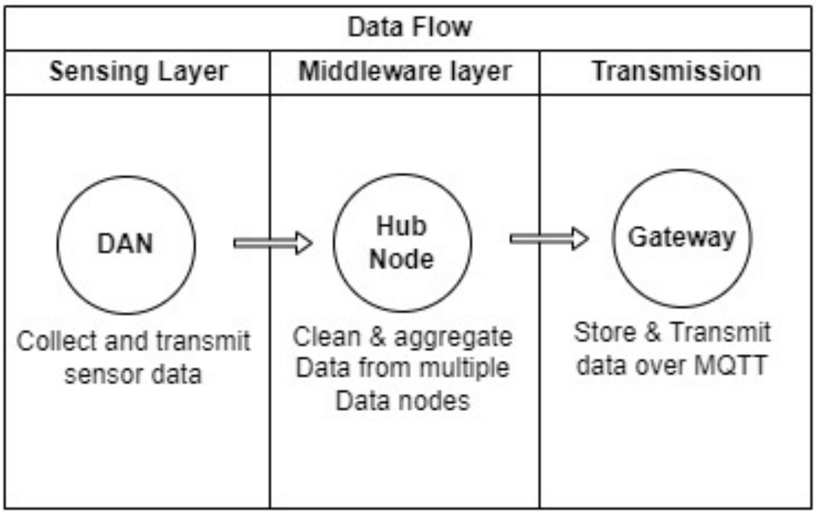



Figure 4.2: Node Data Flow.

### 4.2.1 Data Acquisition Nodes (DANs)

These nodes are responsible for directly sampling vibrations from the bridge at a frequency of 40 Hz. With each node capturing 10 samples per cycle, they collectively gather a substantial volume of data reflecting the dynamic behavior of the bridge. The samples are then sent to the Hub Node.

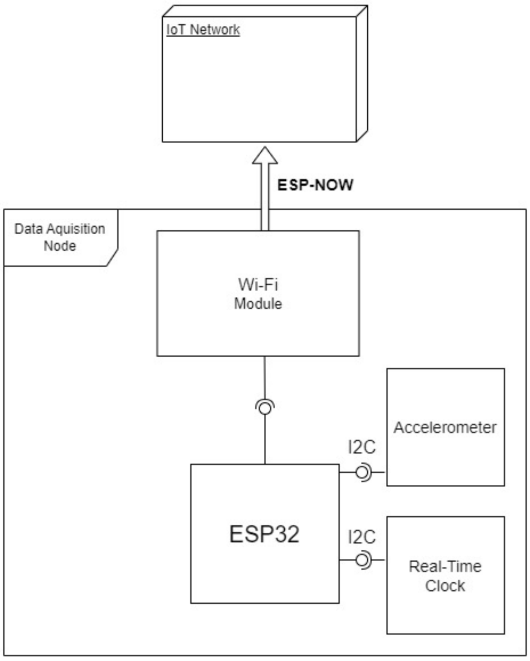



Figure 4.3: Data Acquisition Node (DAN) Architecture.

### 4.2.2 Hub Node:

Acting as a central data repository, the Hub Node receives the sampled data from the DANs. When the data arrives, the Hub Node assigns unique IDs and timestamps to each sample, so that the chronological organization of the data can be maintained. Finally, the Hub Node compiles the organized samples into a CSV file, for subsequent transmission.

### 4.2.3 Gateway Node:

The Gateway Node serves as the connection between the IoT network and the external terminal. Its main task is to acquire the CSV files generated by the Hub Node. Once a CSV file is filled with a predetermined number of samples, 1600 samples per file, the Gateway Node transmits the file. Utilizing the MQTT (Message Queuing Telemetry Transport) protocol, the Gateway Node securely sends the CSV file to the designated terminal for further analysis and storage.

The division of the IoT network into these three nodes allows for a streamlined and efficient data collection and transmission process. The DANs focus on capturing real-time vibration data from the bridge, while the Hub Node ensures proper organization and annotation of the collected samples. Finally, the Gateway Node manages the transfer of aggregated data to the terminal, adhering to predefined criteria for file formatting and transmission frequency.

This design allows for continuous monitoring of the structural health of the bridge, with data being systematically collected, processed, and transmitted to the terminal for in-depth analysis and decision-making.

## 4.3 The ML Model

### 4.3.1 Introduction

The model is an Anomaly Detection model capable of seeking out anomalies based on what is not the norm for the bridge. The dataset we acquired has vibrational data as raw data with samples over timestamps. Additionally, it also gives another information about the number of different types of objects on the bridge upon that timestamp. Our model takes this vibrational data and depicts whether on each timestamp there exists anomaly or not. Potential anomalies can be pretty hazardous for a bridge as it can increase its chances of getting damaged.

### 4.3.2 Data Pre-processing

In data pre-processing we aim to remove as much redundant information as we can. The dataset, which served our purpose for training spanned over 3500 columns and 250 rows with a major chunk of the vibrational data missing. First we tried to remove all the columns which had 80% or more missing values. According to figure 4.4

Most of the columns either had all data or had 10% missing data or were almost empty. After taking care of columns which were mostly empty we get a dataset which is now 500

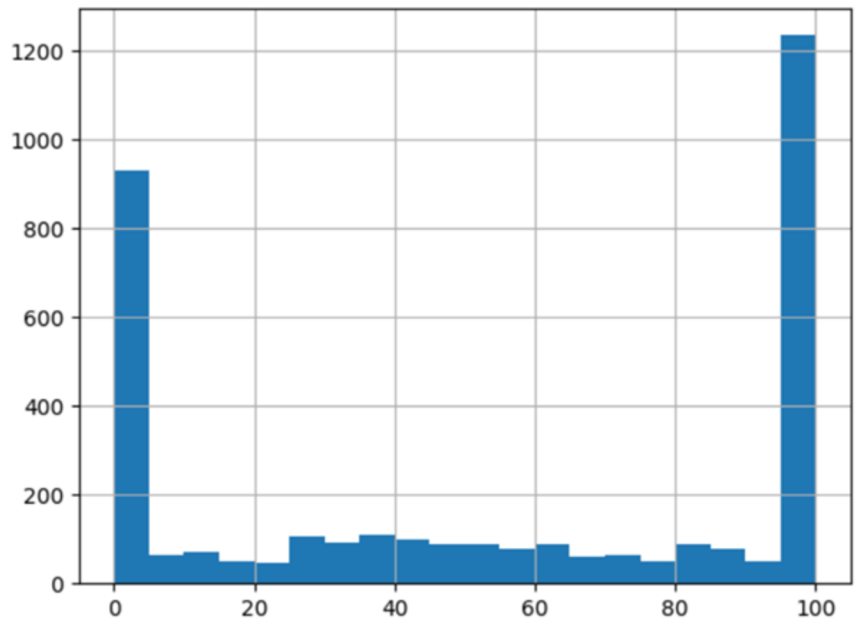



Figure 4.4: Data Preprocessing Stage

columns less. The dataset still had 23.6% data missing but we can't remove more columns as now many columns were moderately filled. Removing them might remove important data for us. As we are leaning towards using Mahalanobis Square Distance (MSD) we now tried to remove highly correlated features which further decreased the number of columns to 2000. From this point we can't remove columns as it would lead to risk losing important data. All other missing values were set to 0 as to not create any bias and can operate on the Autoencoder. Then data was normalized and standardized using Robust Scaler.

### 4.3.3 Feature Learning

We utilized an Autoencoder to compress and then decompress the dataset extracting essential features that capture normal operational patterns. It also reduced the dimensionality of the dataset to 64 columns. The Mean Square Error loss function was used to assess training. In accordance with Mean Square Error (MSE) the training and validation loss significantly decreased till the end, steadily over several epochs. The lack of increase in the validation loss over epochs suggests that the model generalizes well without severe over-fitting. Comparison of validation data's MSE loss and a mean prediction baseline was done and its showed that validation data's MSE loss is significantly lower than mean prediction baseline which means that Autoencoder is capturing and utilizing the information in the data effectively. Robust Scaler showed its significance here as Validation data's MSE was way higher in the case of using Standard Scaler.

### 4.3.4 Mahalanobis Square Distance, Statistical Inference

MSD is a measure derived from the squared difference between a test point and the mean of a sample, weighted by the inverse of the covariance matrix. (Formula put here) MSDs were calculated for each sample. It showed the deviation of each point from what is the norm. By establishing a statistical threshold, set at 95th percentile of the MSD value, we figured out anomalies in accordance to that threshold. Upon testing with data that was based on bridge not with normal health we tweaked the threshold appropriately.

### 4.3.5 Training and Validation

During training, both the training and validation losses significantly decreased over several epochs. The steady decrease without an increase in the validation loss indicates that the model generalizes well and does not suffer from severe over-fitting.

## 4.4 The Cloud

As stated previously, the project incorporates a cloud platfrom for thr data storage, the deployment of the ML model and the visualization of the analyzed data once it is stored back into the system.

### 4.4.1 AWS S3

The first component of the cloud is the storage AWS Simple Storage Service or S3. The data is loaded into S3 from the terminal via a python script. The script continuously monitors arrival of files from the Gateway to the terminal and once it recognizes a new file, it captures the file, and using boto3, uploads the file to S3. From there the file can be accessed by any AWS service that may require it.

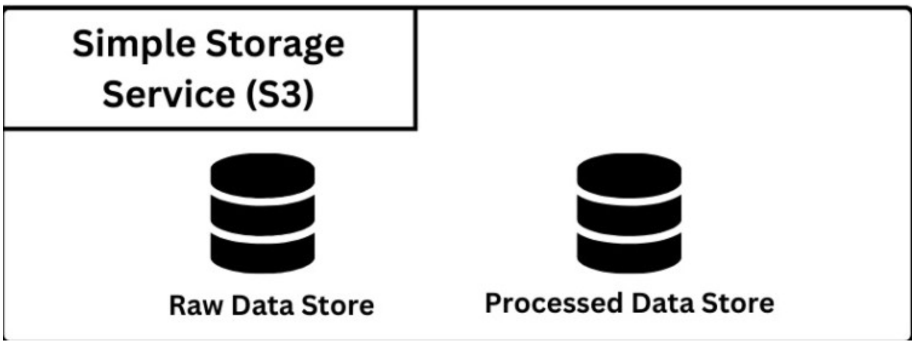



Figure 4.5: AWS S3 Structure.

### 4.4.2 AWS Sagemaker

The second part of the cloud is the ML development environment known as AWS Sagemaker. Here, our model developed in Python and Jupyter Notebooks, is deployed. The working of the model has already been explored. Th deployment on AWS allows the model to quickly retrieve data from S3, analyze it, make a decision and then store it back in S3 for visualization.

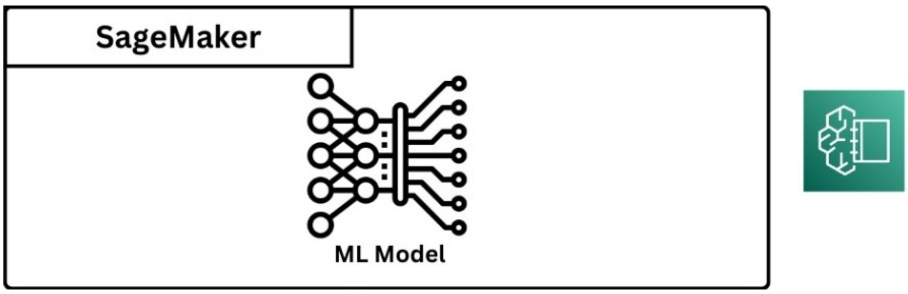



Figure 4.6: AWS Sagemaker Structure.

### 4.4.3 AWS QuickSight

What ties our cloud deployment together is the use of data visualization tools to show real time bridge statistics to the user. For this we use AWS QuickSight data visualization tool. The data is accessed from S3 and with regular intervals, it is refreshed and shown on the dashboard.

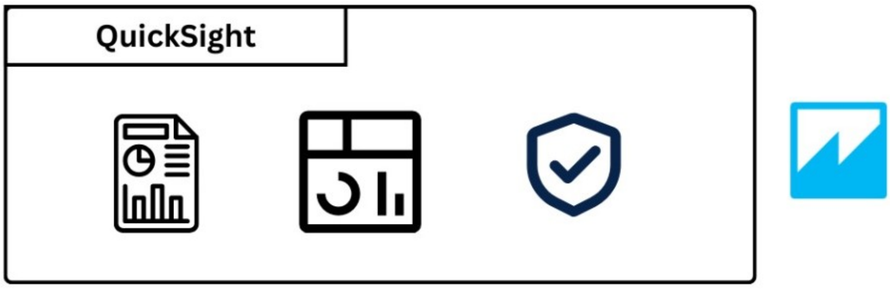



Figure 4.7: AWS Quicksight.

AWS QuickSight allows us to generate pdf reports for record keeping and for sharing with relevant teams. Thus it gets rid of the need for a separate website to maintain the data.

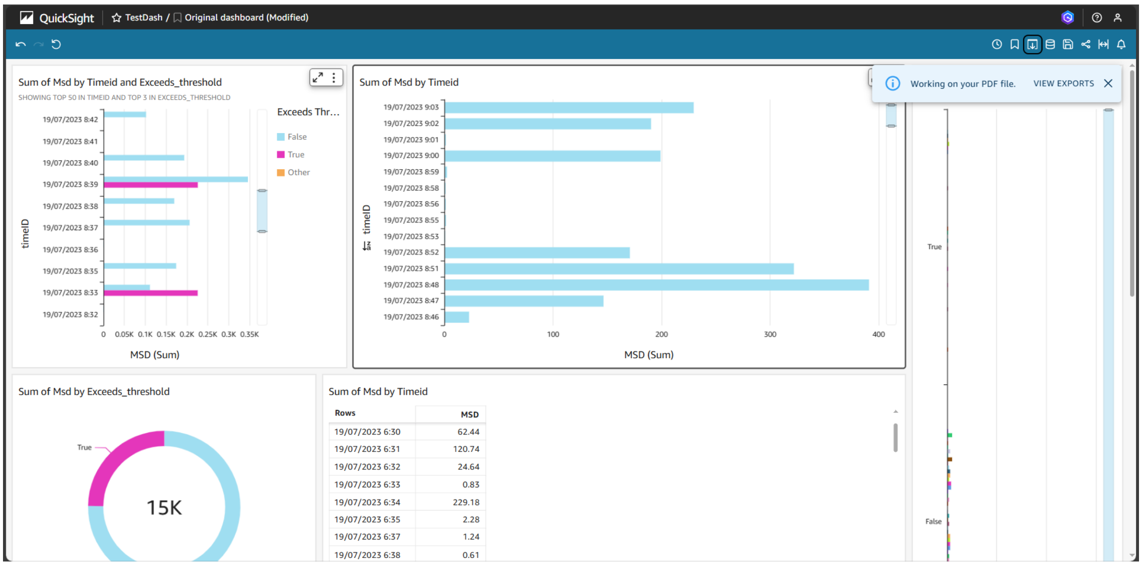



Figure 4.8: AWS QuickSight Dashboard with report generation.

### 4.4.4 IAM User

An IAM user in AWS is an identity within your AWS account that has specific permissions for a single person or application. IAM users can sign in using their account ID or alias, user name, and password. They are not separate accounts but users within your account. IAM allows you to centrally manage permissions for accessing AWS resources

Furthermore, AWS provides data encryption, and native management of users. this eliminates the meed for a separate database for managing user access and worrying about data leaks. Simply create a IAM user from a root user and the IAM use can access read only data from any part of AWS. This allows relevant authorities to limit access to sensitive data and ensure proper security features that may be lacking in external websites. This also eliminates the need to build and maintain the websites, saving resources and manpower.

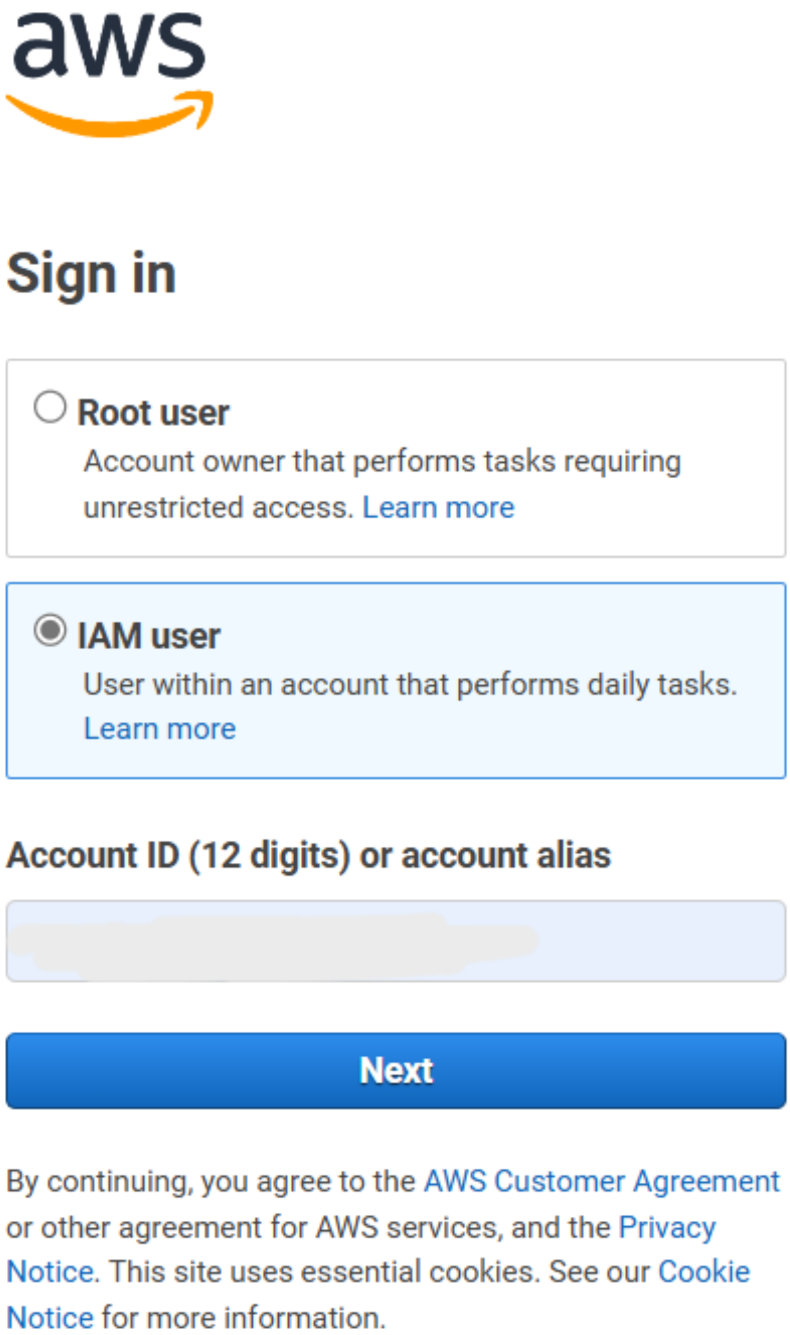



Figure 4.9: IAM user provided by AWS

# Chapter 5

# Deployment & Validation

## 5.1 Introduction

This chapter details the deployment and validation activities conducted for the project. The deployment phase involves the practical application of the system as a pilot project setting, followed by validation to ensure its effectiveness and reliability. This includes steps for deploying IoT network, setting up the cloud infrastructure, implementing the machine learning models, and evaluating the system's performance in a pilot environment.

## 5.2 Deployment

### 5.2.1 Model Bridge

The deployment phase began with the construction of a model bridge for pilot testing and deployment. The model was constructed to simulate structural vibrations of a bridge for data collection and project deployment. The model was constructed as a cable-stayed bridge with a total span of two feet and supported by two pylons.

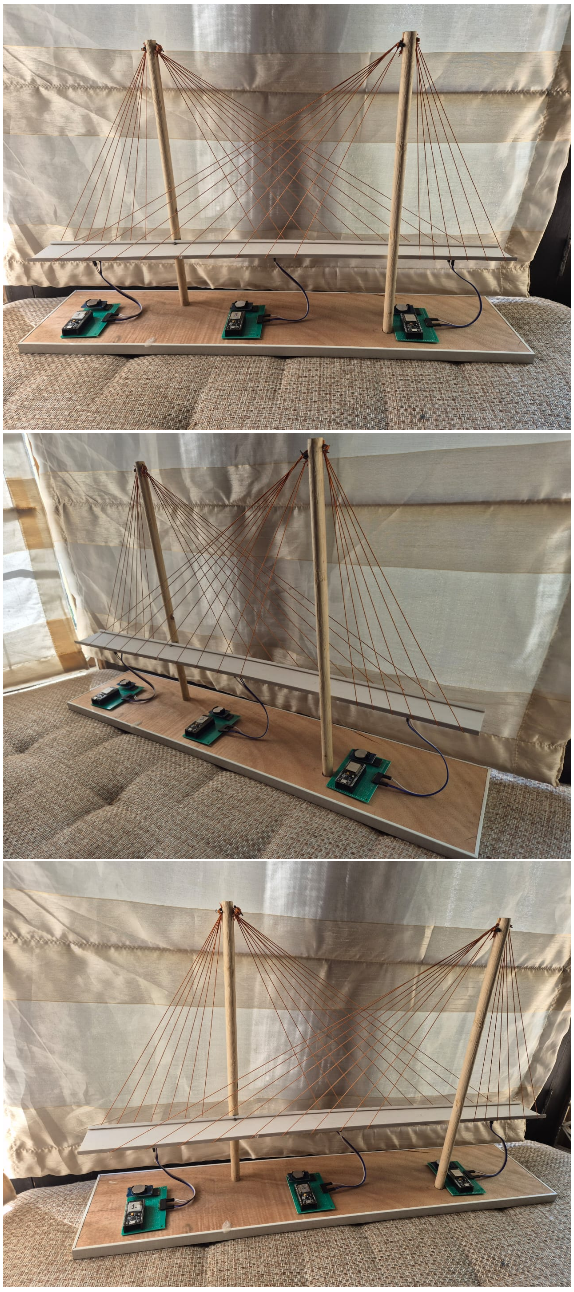


Figure 5.1: The Model Bridge with IoT network deployed

### 5.2.2 IoT Network

The IoT network was deployed over the span of the bridge with a total of three Data Acquisition Nodes (DAN), and a Hub node was deployed for servicing the DANs. The DANs were installed at three locations along the span of the bridge, one was installed at the mid-span and one was installed at each end-span for a total of three DANs. The location of the Hub node is not critical, as with the DAN, however, the Hub must be in range with at least one of the DAN to receive data packets successfully. All nodes were configured to initialize communication over ESP-NOW and supplied with power.

## 5.3 Collection of Data

The data was collected on the model bridge by simulating it with weighted objects. The data was collected both serially and transmitted via MQTT protocol. Each sensor was given it's own folder. The sensor partitioned the data into each dimension and we had to combine into a csv file manually. The data was properly formatted and sent to the cloud for processing.

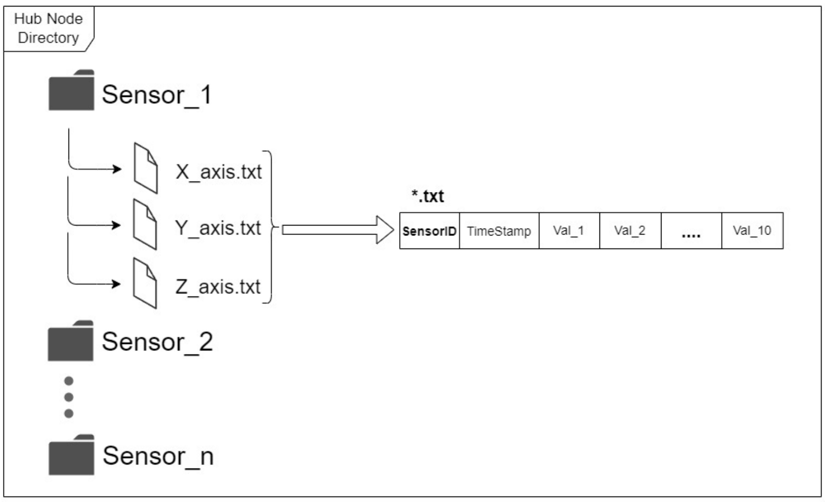



Figure 5.2: Data Collection

## 5.4 ML Model

### 5.4.1 Deployment

The Autoencoder based model is deployed on AWS SageMaker, using it's SageMaker Studio. The studio allows for the model to run continuously and to capture data from S3 or from local repository on PC.

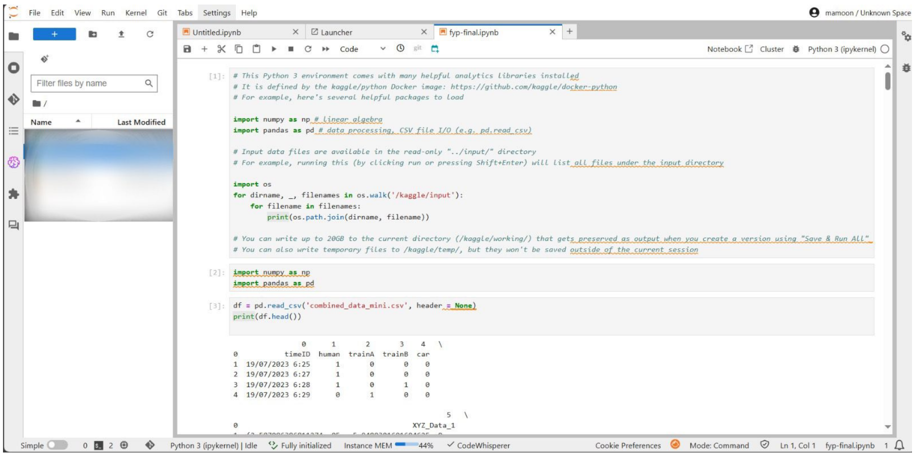



Figure 5.3: Model Environment

### 5.4.2 Results

The results obtained by the model are stored in a CSV file, the file is stored in S3 to be accessed from anywhere in the cloud deployment. The resulting file includes, bridge information, timestamps, MSD values and a label notifying if the bridge function at that moment in time is regular or not.

As we can observe from figure 5.4, the model detects those values that are above our anomaly threshold, and in the basis of that, classifies the function of the bridge at that particular moment of time as regular or irregular.

The resulting CSV file can be observed in Table 5.1.

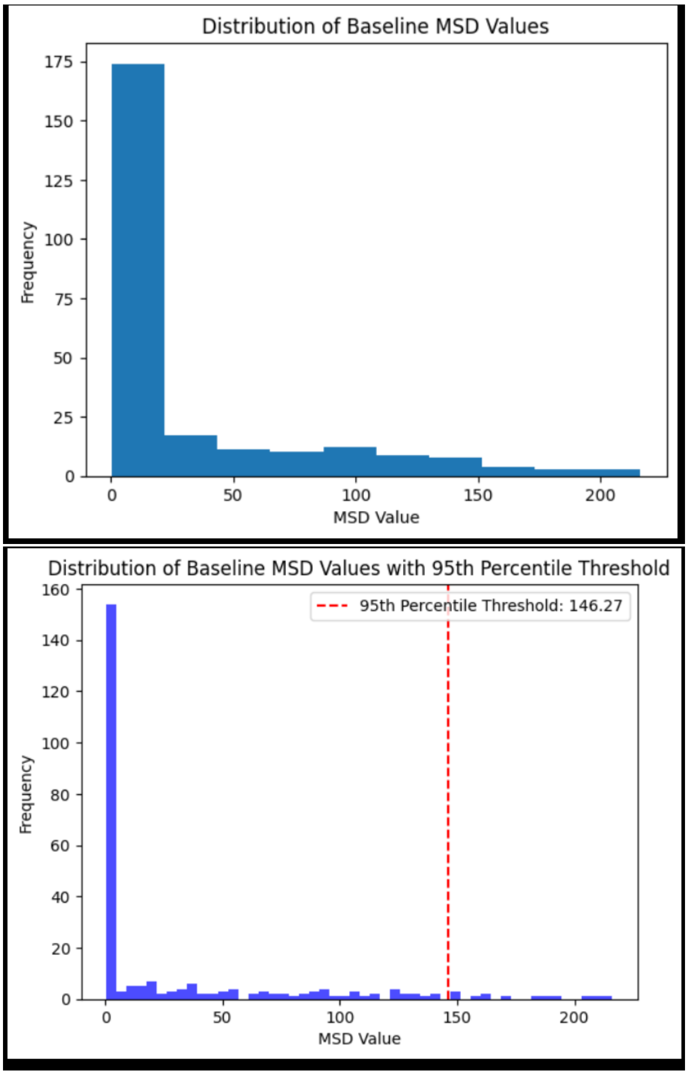


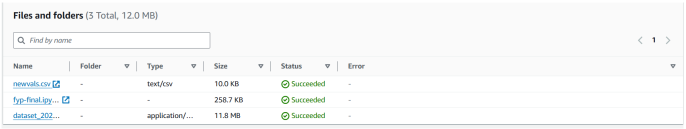

Figure 5.4: Graphical Representation of MSD Outputs

## 5.5 The Cloud

Following are the deployment and results of the cloud deployment of the solution.

### 5.5.1 AWS S3

The data is stored in S3 via an automation script. Once data is done with pre-processing at the PC, it is uploaded to an S3 bucket, similar to the one in Figure 5.5.



Files and folders (3 Total, 12.0 MB)

| Name | Folder | Type | Size | Status | Error |
|---|---|---|---|---|---|
| newvals.csv | - | text/csv | 10.0 KB | Succeeded | - |
| fyp-final.ipy... | - | - | 258.7 KB | Succeeded | - |
| dataset_202... | - | application/... | 11.8 MB | Succeeded | - |

Figure 5.5: Sample S3 Bucket

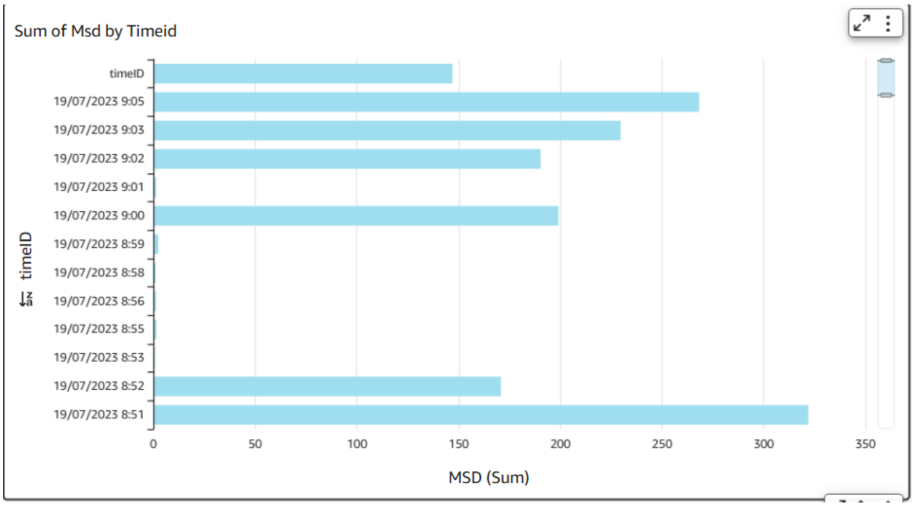



Figure 5.6: All MSDs

### 5.5.2 AWS SageMaker

The ML model is deployed in SageMaker. The environment for the model is the SageMaker Studio by AWS. It has a computing space of 5GB, and is being monitored by AWS, for any faults in the working environment.

### 5.5.3 Dashboard and Visualization

The data is visualized by QuickSight from AWS. It is a strong data dashboarding and visualization tool. QuickSight imports the resulting CSV file from S3 and using graphical tools, builds and deploys a dashboard. The dashboards are highly customized, allowing for users to build their dashboards their own way. Some examples of the dashboard are shown in Figure 5.6 5.7 5.8 and 5.10.

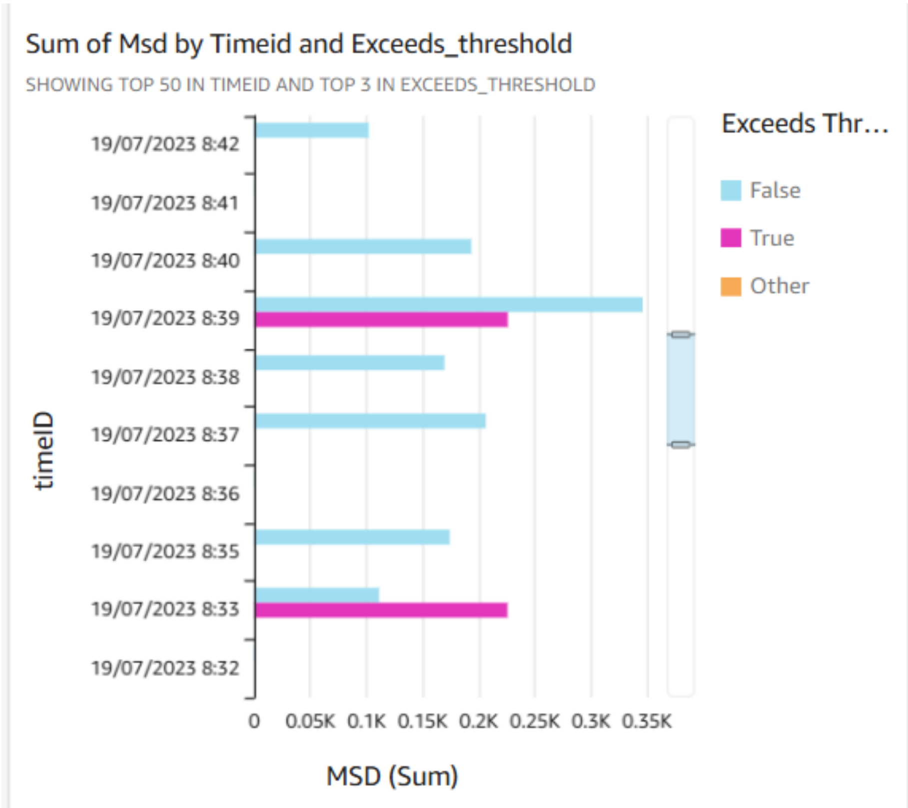



Figure 5.7: MSDs with irregular outputs

| MSD | Exceeds_Threshold | timeID |
|---|---|---|
| 146.9999662 | FALSE | timeID |
| 0.638722716 | FALSE | 19/07/2023 6:25 |
| 185.749329 | FALSE | 19/07/2023 6:27 |
| 193.7629587 | FALSE | 19/07/2023 6:28 |
| 216.4380075 | FALSE | 19/07/2023 6:29 |
| 0.891264145 | FALSE | 19/07/2023 6:29 |
| 61.76090884 | FALSE | 19/07/2023 6:30 |
| 0.682282262 | FALSE | 19/07/2023 6:30 |
| 120.7371598 | FALSE | 19/07/2023 6:31 |
| 0.616487486 | FALSE | 19/07/2023 6:32 |
| 0.780792929 | FALSE | 19/07/2023 6:32 |
| 0.755455204 | FALSE | 19/07/2023 6:32 |
| 22.4846205 | FALSE | 19/07/2023 6:32 |
| 0.827772638 | FALSE | 19/07/2023 6:33 |
| 229.1827672 | TRUE | 19/07/2023 6:34 |
| 1.047348193 | FALSE | 19/07/2023 6:35 |
| 0.620927207 | FALSE | 19/07/2023 6:35 |
| 0.614891153 | FALSE | 19/07/2023 6:35 |
| 0.623676709 | FALSE | 19/07/2023 6:37 |
| 0.617692309 | FALSE | 19/07/2023 6:37 |
| 0.610386199 | FALSE | 19/07/2023 6:38 |
| 50.48856529 | FALSE | 19/07/2023 6:40 |
| 0.653009494 | FALSE | 19/07/2023 6:40 |
| 42.89997181 | FALSE | 19/07/2023 6:40 |
| 4.412945132 | FALSE | 19/07/2023 6:41 |
| 0.740312652 | FALSE | 19/07/2023 6:42 |
| 175.1062879 | FALSE | 19/07/2023 6:43 |
| 192.4000395 | FALSE | 19/07/2023 6:44 |
| 117.6355327 | FALSE | 19/07/2023 6:45 |
| 195.6179468 | FALSE | 19/07/2023 6:46 |
| 122.7654106 | FALSE | 19/07/2023 6:47 |

Table 5.1: The Model Bridge Data

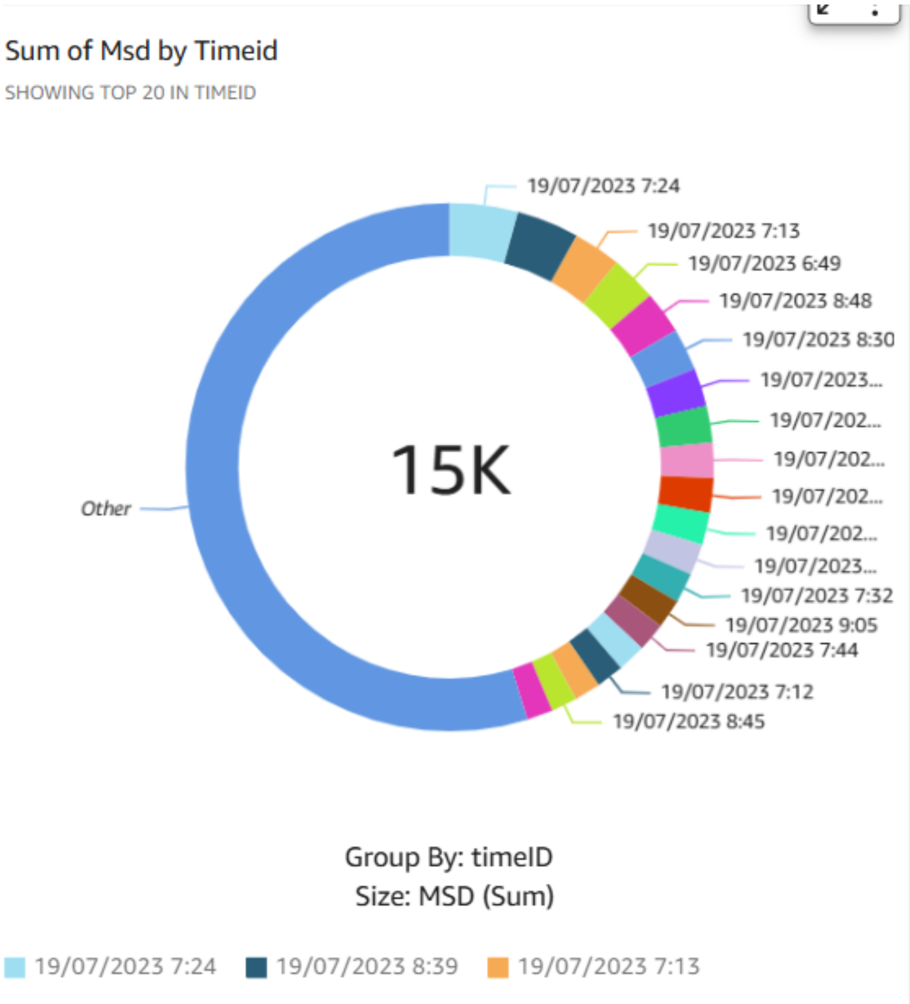



Figure 5.8: Breakdowns by Time

Sum of Msd by Timeid

| Rows | MSD |
|---|---|
| 19/07/2023 6:25 | 0.64 |
| 19/07/2023 6:27 | 185.75 |
| 19/07/2023 6:28 | 193.76 |
| 19/07/2023 6:29 | 217.33 |
| 19/07/2023 6:30 | 62.44 |
| 19/07/2023 6:31 | 120.74 |
| 19/07/2023 6:32 | 24.64 |
| 19/07/2023 6:33 | 0.83 |
| 19/07/2023 6:34 | 229.18 |
| 19/07/2023 6:35 | 2.28 |
| 19/07/2023 6:37 | 1.24 |
| 19/07/2023 6:38 | 0.61 |
| 19/07/2023 6:40 | 94.04 |

Figure 5.9: Sum of MSD by TimeID

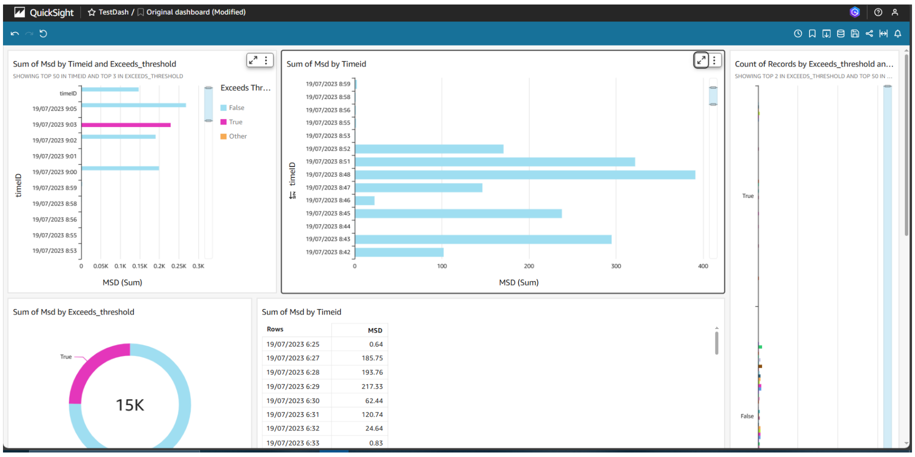



Figure 5.10: Final Dash Sample

# Chapter 6

# Conclusion and Future Work

In this chapter, we will discuss the business side of things, compare it with other pre-existing solutions, conclude the results of this project and propose a direction for the future.

## 6.1 Innovation

### 6.1.1 Technology:

’S.A.F.E’ integrates IoTs, Machine Learning models, and cloud computing technologies for bridge health monitoring.

### 6.1.2 Business Potential:

This idea has the potential to become a startup by selling the DANs to transportation boards and offering customized monitoring dashboards via AWS. This can establish a new standard for bridge maintenance in Pakistan and abroad.

## 6.2 Other Solutions

Here is a list of pre existing SHM solutions for bridges:

### 6.2.1 SMARTEC:

- Uses stress/strain sensors
- Built for concrete bridges
- Targets infrastructure in NA/EU
- Expensive maintenance and deployment

Figure 6.1: SMARTEC LOGO

### 6.2.2 MISTRAS:

- Uses acoustic sensors
- Monitors internal integrity of structures
- Built for cable bridges and pipelines
- Targets infrastructure in NA/EU
- Expensive maintenance and deployment
- Does not provide centralized monitoring tools

Figure 6.2: MISTRAS logo

### 6.2.3 SGS SA:

- Uses image processing and computer vision
- Cannot detect internal faults
- Primary usage is for Wind Turbines and Dams
- Targets infrastructure in SA/SEA
- Expensive maintenance and deployment

Figure 6.3: SGS PVT. LTD.logo

## 6.3 Regional Needs and Solutions

Pakistan, and by extension South Asia, is a vast and developing region. Transportation is the backbone of its economy. Said transport relies on bridges to function properly and be reliable. Sadly, this is not the case for the majority of these nations, where infrastructure maintenance lacks proper checks and administration. Developed nations have tackled this problem using their vast resources, they have developed solutions that allow monitoring of bridges using various technologies. But, these are expensive and not suitable for the needs of South Asian infrastructure.

As we can see from above, existing solutions do not serve the needs for Pakistan, so there is a gap to be closed by someone with the nohow of how these systems work and the willingness to provide this solution.

## 6.4 Our Niche

S.A.F.E aims to tackle this unique problem faced by Pakistan by providing a comprehensive bridge SHM tool, which is user friendly, cheap to deploy and easy to maintain. We want to be able to improve the infrastructure being used in our nation and in neighbouring nations to ensure that delays and costs incured by untimely disasters are avoided.

### 6.4.1 Scalability

Our solution is highly scalable. By using our DANs, we can replicate upto 200 nodes in one network. Also, our model is one fits all, meaning it adjusts to the bridge type and analyzes according to the bridge needs.

### 6.4.2 Cost

Our solution is fairly cost effective. By using accelerometers instead of more complex sensors, we are able to bring our costs down significantly, allowing the solution to be very affordable, specially for developing nations.

### 6.4.3 User Friendly

The use of graphical representation allows for less trained individuals to still understand the conditions of the infrastructure at hand.

## 6.5 SWOT Analysis

| **Strengths** | **Weaknesses** |
|---|---|
| Cost-effective solution | Initial setup and calibration |
| User-friendly interface | Dependency on internet connectivity |
| High scalability | Limited to accelerometer-based detection |
| Integration with AWS | Potential cybersecurity risks |
| **Opportunities** | **Threats** |
| Expansion to other regions | Competition from established SHM providers |
| Partnerships with local governments | Technological advancements from competitors |
| Development of additional sensor integrations | Economic instability in target regions |
| Standardization of SHM practices | Regulatory changes |

Table 6.1: SWOT Analysis

## 6.6 Future Directions

To further enhance the S.A.F.E system, we propose the following directions for future development:

### 6.6.1 Addition of Different Sensors

Integrating various sensors such as strain gauges, thermal sensors, and image-based sensors will enhance the robustness and accuracy of the monitoring system.

### 6.6.2 Maintenance Scheduler

Developing a comprehensive maintenance scheduling tool will help predict and plan maintenance activities, thereby preventing unexpected failures.

### 6.6.3 Collaboration with Local Bodies and Civil Engineers

Working closely with local government bodies and civil engineers will help tailor the solution to specific regional challenges and ensure its practical implementation and acceptance.

### 6.6.4 Enhanced Data Analytics

Incorporating advanced data analytics and machine learning techniques can improve the detection of anomalies and provide deeper insights into the structural health of bridges.

### 6.6.5 Mobile Application Development

Developing a mobile application for on-site inspectors will facilitate real-time data access and reporting, enhancing the overall usability of the system.

## 6.7 Conclusion

The S.A.F.E project presents a pioneering approach to Structural Health Monitoring (SHM) for bridges by integrating IoT, machine learning, and cloud computing. Our system's scalability, cost-effectiveness, and user-friendly interface make it a viable solution for the infrastructure challenges faced by developing nations, particularly in South Asia. Existing SHM solutions are either too costly or lack the necessary features to address the unique needs of this region. S.A.F.E aims to fill this gap, providing a comprehensive and adaptable monitoring tool.

In this report, the Structural Assessment and Forecasting Engine (SAFE) offers an innovative and cost-effective solution for bridge structural health monitoring (SHM) by using a combination of IoT devices, machine learning models, and cloud computing. By deploying Data Acquisition Nodes (DANs) equipped with accelerometers and utilizing a custom autoencoder model, SAFE provides real-time monitoring and predictive maintenance capabilities. The integration of AWS services ensures scalability, reliability, and ease of access, while the focus on cost-effectiveness and user-friendly interface makes it suitable for infrastructure management in resource-constrained regions like South Asia. This approach not only enhances the safety and longevity of bridges but also minimizes the economic impact of structural failures .

To summarise, S.A.F.E has the potential to revolutionize bridge maintenance and monitoring, not only in Pakistan but also in other developing regions. By using advanced technologies and addressing the specific needs of local infrastructure, S.A.F.E can help prevent infrastructure failures, reduce maintenance costs, and improve public safety.

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