Condition Monitoring and Diagnostics of Critical Engineering Asset Using Machine Learning

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CERTIFICATE OF APPROVAL

It is certified that the project titled "CONDITION MONITORING AND DIAGNOSTICS OF CRITICAL ENGINEERING ASSET USING MACHINE LEARNING" carried out by Usama Amjad Reg. No. F19604001, Muhammad Qasim Reg. No. F19604007 and Muhammad Bilal Reg. No. F17604008, under the supervision of Dr. Kamran Javed, National University of Technology, Islamabad, is fully adequate, in scope and in quality, as a capstone project for the degree of BS of Computer Engineering.

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ABSTRACT

This project introduces a novel system for the condition-based monitoring of critical engineering assets, with a specific focus on elevator car doors. By employing machine learning and leveraging custom data acquired through a unique framework using sensor Tile box, the project provides a pioneering approach to real-time fault detection and monitoring.

The absence of relevant datasets necessitated the creation of a custom data collection system, involving on-site sensors to capture accelerometer, temperature, and humidity readings from the elevators. This real-world data enabled an unprecedented level of insight into the operation and potential failures of the elevators. Through meticulous data preprocessing and the identification of fault-related patterns, various car door malfunctions were classified and categorized using standard deviation values on the XYZ axis, with the XGBoost model showing the highest accuracy.

The project also details the development of an intricate back-end system using database, allowing data streaming and management through specific queries. An especially significant contribution is the creation of a comprehensive Human-Machine Interface (HMI) through Grafana. This multi-panel HMI provides both a general overview and in-depth insights into the elevator's operations, including custom error codes and real-time alerts.

Beyond its technical advancements, the project highlights the triumph over challenges related to data collection, pattern recognition, and real-time classification, culminating in a system that enhances both safety and efficiency in elevator operations. Its achievements in custom data collection, real-time monitoring, and intuitive HMI design not only offer immediate applications but also lay the groundwork for future innovations in the integration of machine learning with traditional engineering systems.

Chapter 1

INTRODUCTION

1.1 Background

In today's technological age, transportation plays a vital role in facilitating people's movement from one place to another. Transportation encompasses not only road and air travel but also includes elevators, which are ubiquitous in tall buildings. Elevators are a form of transportation that transports goods and people between floors, saving time and energy that would otherwise be spent climbing stairs. Elevator is a complex mechatronic system comprising numerous components, and its safe and reliable operation relies on the proper functioning of each individual part. However, due to prolonged use, internal components are susceptible to failure. Even a single malfunctioning component can have a significant impact on the safety of the entire elevator system. Therefore, making informed maintenance decisions is crucial not only to reduce the frequency of equipment failures, but also to minimize resource waste and improve the equipment's operational efficiency.

Maintenance has become a crucial aspect of the modern technology world, as it is closely tied to modern production systems and product lifecycle management. Failure to properly maintain machines can lead to their malfunction and result in accidents. According to the New Straits Times, the Department of Occupational Safety and Health (DOSH) has recorded at least 111 elevator-related accidents since 2010, highlighting the need for well-maintained elevators in Malaysia. Unfortunately, many buildings still fall short of the standard for elevator maintenance, which may be due to the high cost of maintenance. Buildings facing financial difficulties may find it difficult to afford the cost of maintenance, leading to inadequate maintenance practices. To prevent accidents and reduce maintenance costs in the long run, it is important to conduct appropriate maintenance on elevators before they malfunction.

There are various types of maintenance strategy systems, Each strategy have their own procedures, but they all aim to extend the life of the machine. Corrective Maintenance, also known as run-to-failure maintenance, is the most common and basic maintenance strategy. This approach only provides maintenance once the machine has broken down and does not provide any prior warning or notice of potential failure. Therefore, applying corrective maintenance to an elevator maintenance system can be very risky. It can be time-consuming and costly to purchase components during an emergency period such as shipping costs.

This makes it vital to avoid using corrective maintenance in elevator maintenance to prevent dangerous and costly outcomes.

Preventive Maintenance has emerged as a vital approach to reducing maintenance costs and achieving sustainable operational management in various industries. The core principle of preventive maintenance lies in utilizing historical data about asset equipment failures to predict and schedule maintenance activities before the occurrence of predicted failures.

The rapid influx of data and the emergence of the industrial internet of things (IIoT) have led to data-driven methodologies taking precedence in manufacturing and mobility solutions, particularly in maintenance and warranty analytics. Terms such as E-maintenance, Maintenance 4.0, or Smart Maintenance are now commonly used to describe the development of approaches aimed at ensuring the integrity of components, products, and systems by analyzing and predicting performance deficiencies that may impact safety.

In this context, machine learning (ML) has played a transformative role, especially in industries like automotive, where vehicles have become increasingly complex systems. With advancements towards automated driving and changes in the drive-train, cost-efficient technical solutions are in high demand to ensure functional safety and reliability over a vehicle's lifetime. ML-based maintenance has emerged as a significant solution approach, attracting extensive research attention due to its ability to exploit the data-rich environment of vehicles and address the challenges posed by their high system complexity.

In this report, we focus on the application of machine learning for condition monitoring and diagnostics of critical engineering assets, specifically in the context of elevator car doors. By leveraging data-driven methodologies and advanced analytics, our project aims to demonstrate how ML-based approaches can revolutionize maintenance strategies, leading to improved asset management, minimized downtime, and enhanced reliability and safety in elevator systems.

1.2 Problem Statement

Elevators are crucial for tall buildings, whether for residential or office purposes. If an elevator unexpectedly breaks down, it can cause inconvenience, casualties, and high maintenance costs. To prevent this, elevators usually use preventive maintenance, which can result in unnecessary work and replacement of parts that still have useful life. However, with a predictive maintenance system, real-time data can be collected using sensors to monitor the elevator's condition and alert users when maintenance is necessary. This strategy maximizes the elevator's lifetime while minimizing the risk of failure and reducing annual maintenance costs.

With this strategy installed, the annual cost for the maintenance will be reduced as the number of times of maintenance is reduced too. It maximizes the lifetime of the elevator while minimizing the risk of elevator failure.

In the context of addressing these challenges, the project aims to develop an advanced maintenance system for elevator car doors. The goal is to leverage cutting-edge machine learning techniques and condition monitoring methodologies to continuously monitor the condition and performance of elevator car doors in real-time.

The primary focus of this project is to implement a data-driven and proactive maintenance approach for elevator car doors. By utilizing machine learning algorithms and real-time sensor data, the project aims to detect early signs of wear, deterioration, or anomalies in elevator car doors. This early detection will enable proactive maintenance actions, extend the operational lifetime of the doors, and enhance the reliability and safety of elevator systems.

By successfully developing and integrating this maintenance system, the project intends to demonstrate the potential of machine learning in revolutionizing maintenance practices for critical engineering assets, specifically elevators. The outcomes of this research have the potential to benefit not only elevator systems but also other industries and infrastructures that rely on efficient and reliable asset management to ensure safety, operational efficiency, and cost-effectiveness.

1.3 Purpose of the Project

In many circumstances, it is financially more sensible to replace parts or components at predetermined intervals rather than to wait for a failure that may result in a costly disruption in operations. Inspections are used to uncover dormant failures. They are also used as part of on-condition tasks to detect impending failures so that PM can be performed. In other words, CBM gives condition of equipment, so that operation remains safe, efficient, and economic. Monitoring techniques are aimed at measuring physical variables that indicate the condition of the machine and comparing these with normal values to determine if the machine is in good condition or deteriorating. CBM focus on data streams from measurable and observable characteristics that are indicators of the condition of the machine, in our case, vehicle and studies the evolution of selected time-dependent parameters by identifying trends that indicate the fault existence, the severity of fault, and the likely run to failure.

Timely decision-making avoids the occurrence of faults and eliminates the possibility of catastrophic failure. In our project, CBM is performed while the machine is running and follows the following process in runtime.

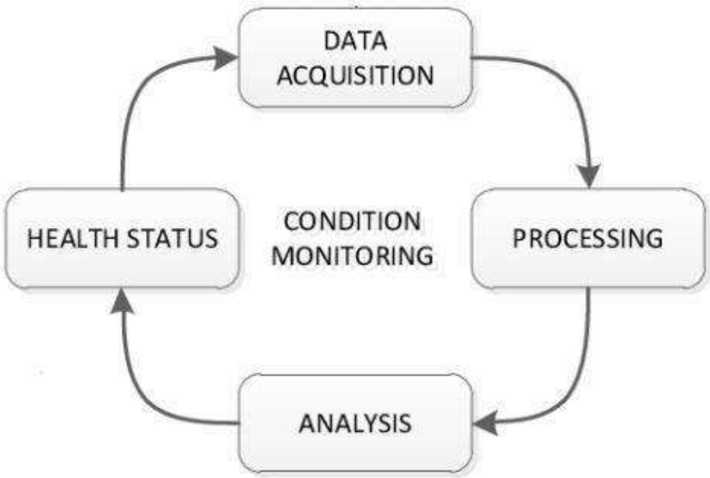


Figure I: Condition Monitoring

Our project relies on the capability to detect failures before they happen so that PM can be initiated. If, during an inspection, the end user (driver) detects warning that the equipment is approaching the end of its life or it has induced another gradually growing fetal error, then it may be possible to delay the failure or prevent it from happening by replace the equipment at the earliest convenience rather than allowing the failure to occur and possibly cause severe consequences.

More specifically, our project is the manifestation of predictive and preventive maintenance approaches that employs monitoring and prediction modelling to determine the condition of the machine and to predict what is likely to fail and approximate the run to failure trends. In contrast to the individually adjusted maintenance interval, where the same maintenance is conducted on a fixed schedule based on mileage or other timing parameter, this approach also determines which component shall be repaired or maintained. Our project utilizes on-board diagnostics featuring fault detection and root cause isolation.

1.4 Motivation

The importance of maintaining elevators cannot be overstated, especially when we consider the shocking statistics of accidents caused by elevator mishaps. According to reports, there were 193 incidents in China between 2015-2018, causing 157 deaths, while the US saw an average of 28 deaths per year due to elevator mishaps. Poor maintenance is the cause of more than 60% of these accidents. In addition to the loss of life, such incidents can expose building owners to legal liability and harm their reputations.

Aside from the safety issues, elevators are expensive expenditures. While a high-end, fully customised elevator might cost over $100,000, the average cost of a simple elevator installation in a business facility can range from $20,000 to $50,000. The average annual cost of elevator maintenance might be between 5 and 10 percent of the initial installation cost. Building owners shouldn't choose neglecting upkeep because it might result in greater repair and even replacement costs.

To avoid accidents and lower maintenance costs, it is essential to establish a reliable method of monitoring elevators. The goal of this project is to create a condition-based monitoring system that can identify possible problems before they become serious and enable preventive maintenance to preserve the dependability and durability of elevators. We want to find patterns and predict probable faults by utilising machine learning algorithms to analyse elevator data, enabling proactive maintenance. The suggested method has the potential to lower maintenance expenses, boost elevator uptime, and improve security. Building residents, tourists, and the general public—who depend on elevators to move safely and effectively within buildings—can also profit from this technology.

1.5 Project Objective

The following are this project's key objectives:

1. Examine and assess important failure mechanisms and potential concerns with elevator car doors.
2. Determine the pertinent sensor information required to efficiently monitor and apply preventive maintenance techniques to elevator car doors.
3. Utilize machine learning techniques to analyse and interpret real-time sensor data to create predictive models for potential problems.

1.6 Significance of the Project

Significant potential benefits for numerous sectors can result from the successful creation of a condition-based monitoring (CBM) system using machine learning techniques for important engineering assets, particularly elevator car doors. The CBM system will support more effective and sustainable infrastructure management by improving the dependability, performance, and safety of elevator car doors. Additionally, this project's methodology and conclusions can be applied to other engineering assets, encouraging the widespread use of CBM and predictive maintenance procedures in a variety of industries.

1.6.1 Economic Benefits:

For enterprises that depend on essential engineering assets, the adoption of a CBM system applying machine learning techniques might result in significant cost reductions. Predictive maintenance and early failure detection help to minimise downtime and the associated expenses from lost production. Effective maintenance planning and resource management also reduce maintenance costs and extend the useful life of assets, providing substantial long-term economic benefits.

1.6.2 Environmental Impact:

The use of a CBM system encourages asset management that is more ecologically friendly. By allowing for prompt replacement of consumables and parts, predictive maintenance helps to cut down on waste production. Additionally, by using the CBM system to optimise energy usage and asset performance, the industry as a whole may lessen its total carbon footprint.

1.6.3 Safety and Quality Improvements:

A key advantage of implementing a CBM system with machine learning techniques is the enhancement of safety and quality in the operation of critical engineering assets. Continuous monitoring of asset health and prediction of potential failures help prevent accidents and equipment malfunctions that could pose risks to personnel and users. Furthermore, improved asset performance and reliability contribute to a higher quality of service and end-user satisfaction.

1.6.4 Scalability and Adaptability:

The methodologies and techniques developed in this project can be easily adapted and scaled to accommodate various types of engineering assets and industries. The flexibility of machine learning algorithms allows the CBM system to be tailored to specific needs and requirements, enabling a wide range of applications and potential future expansions.

1.7 Project Specification

All the modules of this FYP are compiled to achieve high accuracy, coherence, and repeatability. Some specifications are following:

- Elevator car door data is streamed at runtime.
- Data is preprocessed and alerts are generated for each component crossing the healthy threshold.
- Generic Diagnostic trouble codes are classified in run time.
- Error logs are recorded.
- User friendly human machine interface gives detailed insight of performance timeline of each component.
- Alerts are generated in case of component degradation based on similarity analysis.

Real-time alerts and early warnings cut down the cost of unscheduled maintenance while maximizing the component's lifespan, allowing us to obtain more value out of a component by reducing breakdown scenarios through proactive communication by the dealer. It improves customer experience by real-time monitoring of potential faults and saves money on inventory and labor.

1.8 Applications of Project

Solutions provided by our FYP can leverage the construction industry in elevator multi- dimensional data in conjunction with AI techniques to provide insights into every aspect of elevator operation and the timely remote diagnosis of faulty component(s). It benefits:

1. Elevator Remote Monitoring

   This project enables remote monitoring of the elevator health allowing maintenance team to respond pro-actively to potential issues even before they become critical.

2. Elevator Safety Enhancement

   Our ML can help identify potential safety hazards by analyzing elevator behavior and detecting deviations from safety protocols.

3. Elevator Predictive Maintenance

Our ML Algorithm can analyze sensor data from elevators to predict when maintenance is required, helping to prevent unexpected breakdowns, and reducing downtime.

1.9 Sustainable Development Goals (SDGs)

The integration of predictive analytics in the elevator industry holds immense potential, offering significant cost and time savings through predictive maintenance while prioritizing operator safety and reducing operational stress. The real-time health monitoring of elevator car doors not only optimizes emissions filtration but also enhances efficiency, promoting greater environmental sustainability. Such advancements in maintenance align with the objectives of two Sustainable Development Goals (SDGs), specifically, SDG 9: Industry, Innovation, and Infrastructure, and SDG 11: Sustainable Cities and Communities.

This project aligns with SDG 9 by contributing to the development and enhancement of sustainable infrastructure and fostering innovation. By implementing an advanced maintenance system for elevator car doors, the project aims to improve the reliability and efficiency of critical engineering assets, which are integral to modern infrastructure. Through the utilization of machine learning techniques, the project seeks to optimize maintenance practices, reduce downtime, and extend the operational lifetime of elevators, thus contributing to the creation of resilient and sustainable infrastructure for vertical transportation in buildings.

The project also supports SDG 11 by addressing the goal of creating sustainable cities and communities. Elevators are essential components of urban infrastructure, enabling efficient vertical transportation in tall buildings for residential, commercial, and public use. By implementing a data-driven condition monitoring system, the project aims to enhance elevator safety, reliability, and performance, contributing to improved urban mobility and convenience. The proactive maintenance approach adopted in this project will lead to reduced disruptions in elevator services, better accessibility for residents and visitors, and a safer living environment. Ultimately, by promoting the sustainable management and maintenance of elevator systems, the project plays a role in building inclusive, safe, and resilient cities that offer a high quality of life to their inhabitants.

1.10 Project Timeline

The project work-up plan was scheduled based on university requirements in which it was specified that hardware and software tools identification, literature review and design finalization was to be done in 7th semester. In the 8th semester implementation, integration and use case evaluations were to be done.

The following Gantt Chart represents details about our FYP project plan:

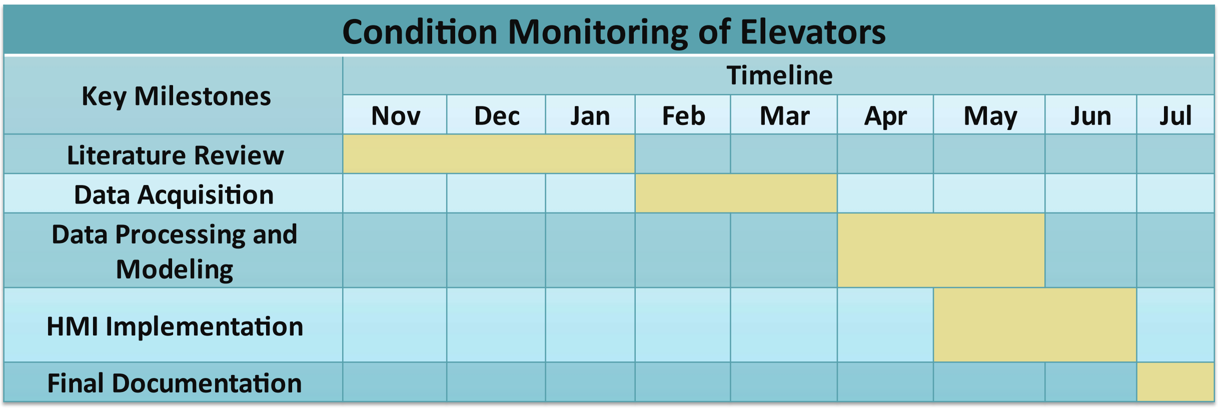


Figure II: Gantt Chat

1.11 Report Organization

1.11.1 Chapter 1 (Introduction)

Chapter 1 of the report is about the introduction of our FYP and its application in construction industry and its basic terminologies, problem statement, overview of what we have done and achieved in this FYP, design specifications, applications and finally project plan is given.

1.11.2 Chapter 2 (Literature Review)

Chapter 2 of the report is discussion about all the previous work done on elevator health monitoring and maintenance system and research papers studied to get an idea about previous research and ongoing research being done on Elevator Health Monitoring.

1.11.3 Chapter 3 (Hardware & Software Specifications)

Chapter 3 of the report is a discussion about all the details of hardware and software components used to implement the project.

1.11.4 Chapter 4 (Project design & Implementation)

Chapter 4 of the report is discussion about all the details of framework of the project which included designing and implementation of the project.

1.11.5 Chapter 5 (Project Results)

Chapter 5 of the report is a discussion about the outcomes, results concluded after project implementation.

1.11.6 Chapter 6 (Conclusion)

Chapter 6 of the report is a discussion about the problems faced during the implementation of the proposed project design and future goals regarding the project.

Chapter 2

LITERATURE REVIEW

Terminologies from “Industry 4.0” can be derived for categorization of maintenance according to the level of maturity from maintenance 1.0 (corrective maintenance) to maintenance 4.0 comprising advanced data-driven methods, and methods estimating the probability of failures and their effects (reliability centered maintenance) [5]. Since this project is based on machine learning (ML) for preventive maintenance, in this section, the ML fundamentals relevant for data analytics and preventive maintenance are reviewed and their relationship is explored.

2.1 Type of Maintenance

There are various types of maintenance strategy systems, but the three main strategies are Corrective Maintenance, Preventive Maintenance, and Predictive Maintenance. These strategies have their own procedures, but they all aim to extend the life of the machine.

2.1.1 Corrective Maintenance

Corrective Maintenance, also known as run-to-failure maintenance, is the most common and basic maintenance strategy. This approach only provides maintenance once the machine has broken down and does not provide any prior warning or notice of potential failure. Therefore, applying corrective maintenance to an elevator maintenance system can be very risky. It can be time-consuming and costly to purchase components during an emergency period such as shipping costs. This makes it vital to avoid using corrective maintenance in elevator maintenance to prevent dangerous and costly outcomes.

2.1.2 Preventive Maintenance

Preventive Maintenance is a maintenance strategy that relies on knowledge of the machine, engineer experience, and data from similar machines. Based on this data, a schedule is set for checking the machine, which can be daily, weekly, monthly, or annually. Engineers check the machine during these scheduled visits to determine if any components need to be repaired or replaced. The advantage of this strategy is that users know when the machine needs to be serviced, and all preparation work can be done before maintenance, minimizing disruption. However, the disadvantage of preventive maintenance is that parts that are replaced during maintenance may still have usable life left, resulting in unnecessary replacement costs. Additionally, the cost of preventive maintenance can be high due to the replacement of parts that are still usable and unnecessary maintenance checks when the machine is in good condition.

2.1.3 Predictive Maintenance

Predictive Maintenance is the latest and most well-known maintenance strategy that aims to maximize the lifetime of the machine while minimizing the risk of machine failure. This strategy reduces the number of times the machine needs to be serviced, resulting in lower annual maintenance costs. The philosophy behind this strategy is "execute at the right time," meaning that maintenance and actions are only taken when necessary. To implement predictive maintenance, big data is required to collect real-time data for diagnosis. Researchers have proposed a big data-based predictive maintenance architecture for biomedical devices in the health domain. This system predicts the Remaining Useful Life (RUL) of the machine and makes a final decision on the maintenance required for the machine.

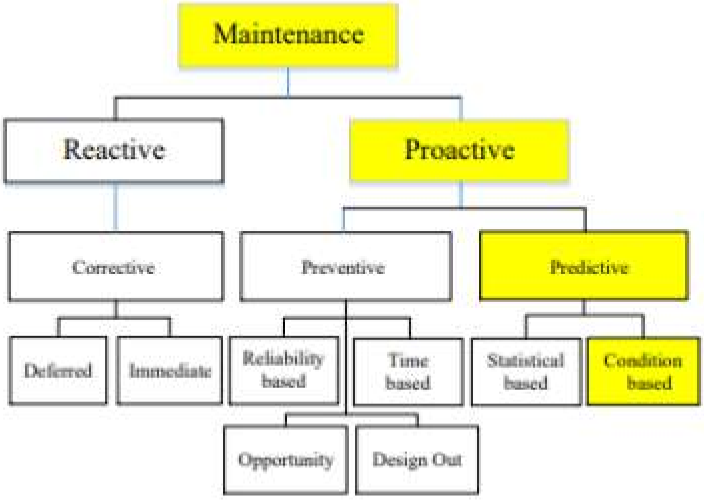


Figure III: Types of Maintenance

2.2 Condition-Based Maintenance

CBM aims to determine the condition of equipment, so that operation remains safe, efficient, and economic. Monitoring techniques are aimed at measuring physical variables that indicate the condition of the machine and comparing these with normal values to determine if the machine is in good condition or deteriorating. CBM assumes there are measurable and observable characteristics that are indicators of the condition of the machine.

Condition monitoring studies the evolution of selected time-dependent parameters; it identifies trends indicating the existence of a fault, its severity, and the likely time to failure (TTF). Timely decision-making avoids the occurrence of faults and eliminates the possibility of catastrophic failure. CBM can be performed while the machine is running (Gerardo Trujillo and América, 2003). CBM consists of three key steps:

Figure IV: Condition based maintenance

I. Data acquisition (information collecting), to obtain data relevant to system health.
II. Data processing (information handling), to handle and analyze the data or signals collected in step 1 for better understanding and interpretation of the data.
III. Maintenance decision-making (decision-making), to recommend efficient maintenance policies.

The last step of a CBM program is maintenance decision-making. Sufficient and efficient decision support is crucial for determining maintenance actions. Techniques for maintenance decision support in a CBM program can be divided into two main categories: diagnostics and prognostics. Fault diagnostics focus on detection, isolation, and identification of faults when they occur. Prognostics attempt to predict faults or failures before they occur.

Obviously, prognostics are superior to diagnostics in the sense that prognostics can either prevent faults or failures or be ready (with spare parts and human resources) for the problems, thus reducing the costs of unplanned maintenance.

Nevertheless, prognostics cannot completely replace diagnostics since, in practice, there are always some faults and failures, which are not predictable. In addition, prognostics, like any other prediction technique, cannot be 100% accurate. In the case of unsuccessful prediction, diagnostics can be a complementary tool for maintenance decision-making. Diagnostics are also helpful for improving prognostics; diagnostic information can result in more accurate event data, and a better CBM model can be built for prognostics. Furthermore, diagnostic information can be used as feedback information for system redesign.

2.3 Critical Engineering Asset

The selection of an appropriate engineering asset for the focus of our project holds paramount significance as it determines the real-world impact and applicability of our research. After careful consideration, we have chosen the Elevator Car Door as the primary asset of interest. Elevators are indispensable components of urban infrastructure, facilitating efficient vertical transportation in buildings and public spaces. Among various elevator components, the Elevator Car Door stands out as a critical engineering asset due to its pivotal role in passenger safety and overall elevator performance. A malfunctioned car door presents significant operational and safety issues, making it an excellent subject for our study. We seek to improve safety, maximise operational effectiveness, and contribute to the sustainable management of contemporary urban infrastructure by tackling the issues related to elevator car doors through data-driven insights and sophisticated condition-based monitoring.

2.3.1 Elevator Car Door

A key interface allowing people to enter and depart elevator cabins safely and effectively, the elevator car door is an integral part of contemporary urban infrastructure. The elevator car door is a vital piece of technical equipment that is essential to the safe and efficient operation of elevators in commercial buildings, offices, and public areas. For passenger safety, operational effectiveness, and general building accessibility, it must operate well.

When considering elevator car doors as a crucial engineering component, safety comes first. To avoid any mistakes or accidents, the doors must be built and maintained to fulfil strict safety regulations. Passengers could be seriously injured or entrapped as a result of a malfunctioning door. Therefore, routine checks, upkeep, and predictive monitoring are necessary to spot any problems early on and fix them before they become safety threats.

Another important component of elevator car doors as important engineering assets is operational efficiency. In order to reduce passenger wait times and improve the flow of passengers entering and exiting elevators, quick and dependable door opening and shutting mechanisms are essential. Any hiccups or delays in door operation might affect traffic flow inside the facility, lower productivity, and annoy users. Therefore, ensuring the elevator car doors operate smoothly is essential for effective building administration and user pleasure.

Given the substantial influence elevator car doors have on the user experience and building operations, condition-based monitoring that makes use of cutting-edge technology like machine learning and sensor data analysis is becoming more and more valuable. The ability to forecast probable failures and keep track of the general condition of elevator car doors is made feasible by gathering real-time data from a variety of sensors, including temperature, humidity, and accelerometers. Building managers may proactively schedule maintenance tasks and minimise unplanned downtime using data-driven insights and predictive maintenance tactics, ensuring that the elevator car doors are always functional and secure.

2.4 Related Work

The review of the literature offers a summary of the current studies on elevator maintenance and the application of CBM systems across different industries. The review focuses on the problems with conventional elevator upkeep, as well as the approaches, algorithms, and strategies used in the research publications and their applicability to our project.

2.4.1 Paper 1

"Research on Preventive Maintenance Strategy of Elevator Equipment" by Hongjiu Liu and Jiaxuan Wu

Research on preventive maintenance strategies and procedures for elevator equipment is the major topic of the paper "Research on Preventive Maintenance Strategy of Elevator Equipment" by Jiaxuan Wu and Hongjiu Liu. By examining maintenance procedures, determining maintenance intervals, choosing the best maintenance contractors, and keeping an eye on key components for the early detection of abnormal circumstances, the studies seek to increase elevator performance, reliability, and safety. In the real estate market, where there are more elevator accidents than ever before, the study underlines the value of preventive maintenance of elevator equipment. An ideal maintenance plan for elevators is suggested in the study to lower the failure rate. The model's goal is to keep a particular level of reliability while minimising the average maintenance cost. The determination of the failure rate function, optimization of unplanned maintenance costs, and shutdown costs are also covered in the article. The study proposes an elevator maintenance mathematical model that takes into account the expenses and losses related to maintenance and downtime. A case study is presented to show the usefulness of the model, which determines the best maintenance plan using improvement factors and genetic algorithms. According to the study, the ideal number of preventive maintenance cycles grows along with the reliability requirements. The study suggests that additional investigation is required to examine the connection between various pieces of equipment. The literature study also examines several research on the dependability and security of elevators as well as the significance of maintaining and caring for manufacturing equipment. The studies investigate several maintenance approaches, including preventative maintenance and breakdown repair, and take into account elements like resource development, power loads, and the degree of actual workload. It is also addressed how simulation modelling methods and mathematical models are used.

2.4.2 Paper 2

" Preventive maintenance period decision for elevator parts based on multi-objective optimization method" by Dapeng Niu , Lei Guo , Xiaolin Bi, Di Wen

A preventive maintenance model for elevator components is covered in the paper "Preventive maintenance period decision for elevator parts based on multi-objective optimization approach" by Dapeng Niu, Lei Guo, Xiaolin Bi, and Di Wen. A mixed failure rate model for elevator components is used in the model, which takes into account both the age reduction factor and the failure rate raising factor. Based on the cost variables of preventative maintenance, repair after failure, and downtime caused by maintenance and repair procedure, a multi-objective optimization model is utilised to determine the maintenance period of elevator parts. The ideal maintenance period is determined using the Monte Carlo simulation method. The defect record data for elevator parts is applied to the model, and the results of parameter estimation are provided. In order to create a multi-objective optimization model to determine the maintenance interval for elevator parts, the paper describes the use of Weibull distribution technology to analyse failure data of elevator component failures. The model determines a reasonable maintenance cycle that minimises costs and maximises utilisation rate by taking into account time factors such as utilisation rate, cost factors such as preventive maintenance costs, post-repair costs, and downtime loss costs, and cost factors such as downtime costs. The suggested approach is anticipated to lower the possibility of equipment failure and prevent excessive resource waste. The Fundamental Research Funds for the Central Universities and the National Key Research and Development Program of China both provided funding for the study. The decision-making process for figuring out how long elevator parts should be maintained is presented in this paper. The process entails looking at historical fault data for elevator parts to build a component failure distribution law model. To account for the effect of maintenance and repair on parts, the age reduction factor and the failure rate raising factor are introduced. On the basis of the failure rate function, the age reduction factor, and the failure rate raising factor, a mixed failure rate model is created. With maintenance frequency serving as the decision variable, a multi-objective optimization model is constructed and then solved using a Monte Carlo simulation approach. The results demonstrate the efficiency of the suggested strategy in lowering the risk of equipment failure and saving money as it is used to determine the ideal maintenance frequency for elevator parts.

2.4.3 Paper 3

" Decision Making for Predictive Maintenance in Asset Information Management" by R. B. Faiz and Eran A. Edirisinghe

R. B. Faiz and Eran A. Edirisinghe discuss various decision support techniques for asset management in their work , "Decision Making for Predictive Maintenance in Asset Information Management." It contrasts knowledge-based systems, case-based reasoning, fuzzy logic, and predictive maintenance in addition to manual and automated decision-making. The writers highlight the significance of precise asset information while discussing the benefits and drawbacks of each strategy. The study discusses research trends, applications of artificial intelligence, and scheduling methods in rail network asset management. It focuses particularly on decision-making for predictive maintenance of train network assets, contrasting proactive versus reactive scheduling, and suggesting the incorporation of expert systems and fuzzy logic to enhance decision-making. The need of sound decisions supported by efficient asset information management is emphasised by the writers. Future directions are also discussed, including the application of decision support systems and more flexible expert systems. Overall, the study offers insightful information on how diverse industries can make efficient asset management decisions.

2.4.4 Paper 4

" Predictive maintenance on an elevator system using machine learning " by Law Jing Shen, Jacqueline Lukose, Lau Chee Young

The study on the use of machine learning techniques for proactive maintenance on an elevator system is presented in the paper. According to the authors, conventional maintenance techniques like reactive maintenance and periodic maintenance are insufficiently effective to meet the demands of contemporary elevator systems. Therefore, predictive maintenance can be a better solution to optimize maintenance schedules, reduce maintenance costs, and prevent unexpected system failures. The scientists trained numerous machine learning models using a dataset of elevator system parameters, such as motor temperature, door opening and closing timings, floor level, and time of day. To find the best model for predictive maintenance, they analysed the performance of different models, including Decision Trees, Random Forest, and Neural Networks. The study's findings demonstrated that the Random Forest model was the most accurate at estimating the probability that the elevator system would malfunction. The most critical aspects of the system's operation, such as motor temperature and door opening and shutting times, could be identified by the model, which also offered maintenance advice based on the seriousness of the anticipated failure.

2.4.5 Paper 5

" Elevator Leveling Failures Monitoring Device and Method" by R. Z. Sun, X. A. Wang, Y.Z. Cai and J. M. Cao

The relevance of elevator safety and the necessity of efficient monitoring of elevator levelling failures are both covered in the opening section of the article. The authors point out that the levelling of the elevator vehicle with regard to the floor is now monitored by mechanical or electrical sensors, but these sensors are subject to failure or malfunction, which might result in accidents. The authors suggest a novel monitoring system that combines a vibration sensor, a microprocessor, and a wireless communication module to address this problem. The microprocessor interprets the data, delivers it wirelessly to a distant server for analysis, and uses the vibration sensor to detect elevator movement. In order to examine the data and find levelling issues, the authors also suggest a machine learning-based approach. The monitoring system effectively detects elevator levelling issues, according to studies the authors conducted to assess its efficacy. The ability of the equipment to distinguish between typical elevator performance and breakdowns enables prompt maintenance and repairs. Additionally, the scientists carried out a comparison study using current elevator sensors and discovered that their suggested technology is more effective at spotting levelling errors. The potential uses of the suggested monitoring device in different kinds of elevators, such as passenger elevators, freight elevators, and high-speed elevators, are covered in the paper. According to the authors, the proposed technology is simple to integrate into current elevator systems and has the potential to lower maintenance expenses while also increasing elevator dependability. In order to detect elevator levelling failures, the proposed monitoring device and method are effective, and the paper finishes by summarising the research's contributions and outlining potential future research areas for elevating elevator safety.

2.4.6 Paper 6

" Elevator Running Fault Monitoring Method Based on Vibration Signal" by Xiongfei Gao ,Hongru Li, and Hali Pang

The relevance of elevators in contemporary structures and the demand for dependable and effective monitoring systems are covered in the opening section of the essay. The authors then go into their suggested monitoring technique, which is based on looking at the vibration signals the elevator produces while it is operating. The proposed monitoring system, which entails employing sensors to gather vibration data from the elevator and various signal processing techniques to process the signals, is thoroughly described in the study. The main characteristics of the vibration signals—such as those utilised to recognise motor bearing defects, traction sheave faults, and guide rail faults—are covered by the authors. The proposed monitoring system for identifying and diagnosing elevator defects is shown to be effective in the paper's experimental results. The research also addresses the benefits of the suggested approach over other elevator monitoring strategies, such as acoustic monitoring and visual inspection. The authors emphasise the vibration signal-based monitoring method's high sensitivity and accuracy as well as its capacity to identify flaws early on, which can help save expensive repairs and raise the general safety and dependability of elevators.

2.4.7 Paper 7

" Preventive maintenance period decision for elevator parts based on multi-objective optimization method" by Dapeng Niu, Lei Guo, Xiaolin Bi, Di Wen

In addition to highlighting the difficulties in deciding on the ideal maintenance interval, the study discusses the value of preventative maintenance in the elevator sector. In order to address these difficulties, the authors formulate the issue as a multi-objective optimization problem. The proposed method takes into account both system reliability and maintenance costs. To address the optimization problem and find the Pareto optimal solutions, the authors employ a genetic method. The trade-off solutions between the two objectives are represented by the Pareto optimum solutions. The authors conduct experiments on a case study of an elevator system to verify the suggested approach. The findings demonstrate that the suggested method is successful in identifying the ideal interval for preventative maintenance on elevator parts.

2.4.8 Paper 8

“Implementing Deep Learning Model to Predict the Maintenance of an Elevator System” by Gaayan Verma, Jasmine Awatramani, Nitasha Hasteer

The implementation of a deep learning-based predictive maintenance algorithm for defect detection and prediction of an elevator system is presented in the paper Implementing Deep Learning Model to Predict the Maintenance of an Elevator System by Gaayan Verma, Jasmine Awatramani, and Nitasha Hasteer. The significance of elevators in our daily lives is emphasised in the paper, as is the requirement for appropriate maintenance to ensure their safe and effective operation. The authors point out that predictive maintenance can assist in determining the ideal window for maintenance and save expensive downtime. The implementation of an LSTM algorithm on a collection of sensor data captured during maintenance activities is shown in the study, which yielded a mean absolute error of 7.05 percent. The advantages of deep learning for predictive maintenance are also covered by the paper's authors. They point out that without explicit feature engineering, deep learning models can extract new features from data. As a result, the models are more trustworthy and simpler to apply to new situations. The writers also go over the value of doing elevator system maintenance in a timely manner as well as the advantages of automating the process with predictive maintenance.

Chapter 3

HARDWARE AND SOFTWARE SPECIFICATIONS

HARDWARE TOOLS

The hardware components of our senior project are presented in this chapter, with a particular emphasis on the implementation of the Sensor Tile and its integration into our asset, the "STEP c7000 Elevator." The Sensor Tile, a small and adaptable platform that offers crucial data collecting capabilities through a variety of cutting-edge sensors, serves as the basis of our project. In this chapter, we will examine the important characteristics and technical details of the sensor tile and its sensors, including the Bluetooth Application Processor v5.2, the 3-axis Accelerometers (LIS2DW12 and LIS3DHH), the Digital Temperature Sensor (STTS751), and the Humidity Sensor (HTS221) (BlueNRG-M2). By utilising the potential of these sensors and seamlessly combining them into the "STEP c7000 Elevator," we seek to enhance the overall functioning, safety, and efficiency of this vital transportation asset. This chapter provides a thorough description of the hardware elements essential to the completion of our senior project.

3.1 Elevators

The centerpiece of our senior project is a cutting-edge elevator system called the "STEP c7000 Elevator." This cutting-edge elevator model was created with a heavy emphasis on user experience, efficiency, and safety. The "STEP c7000 Elevator," which is outfitted with cutting-edge technology and novel features, intends to transform vertical transportation in contemporary buildings.

The "STEP c7000 Elevator" was designed with safety as its first priority. To ensure passenger safety, it includes a wide variety of safety sensors and redundant systems. These safety features include emergency stop buttons, door edge sensors, and a sophisticated braking mechanism that effectively stops the elevator in an emergency.

The "STEP c7000 Elevator" has a regenerative drive system, which maximizes efficiency by recovering energy during braking and using it to propel the elevator upward. By limiting overall energy waste, this energy-efficient function not only lowers power consumption but also promotes environmental sustainability.

The incorporation of cutting-edge sensing technologies improves the elevator's user experience. In order to ensure that passengers have a comfortable and hassle-free ride, our project will employ sensor data to optimize the elevator's performance, give users real-time information regarding cabin occupancy, and forecast maintenance requirements.

Figure V: STEP C7000 Elevator

3.2 Sensor Tile (STEVAL-MKSBOX1V1)

As the nucleus of our hardware implementation, the Sensor Tile model STEVAL-MKSBOX1V1 acts as a small, flexible platform for data collecting and integration into the "STEP c7000 Elevator." This sophisticated module has a variety of cutting-edge sensors that allow us to gather crucial information for thorough elevator health monitoring and diagnostics.

3.2.1 Specifications and Features:

The STEVAL-MKSBOX1V1 Sensor Tile has a compact and modular design that makes it simple to integrate into the elevator's current infrastructure. Due to its compact size, installation is simple and won't significantly affect how the elevator functions.

- **Sensor Diversity:**
  The Digital Temperature Sensor (STTS751), 3-axis Accelerometers (LIS2DW12 and LIS3DHH), Humidity Sensor (HTS221), and Bluetooth Application Processor v5.2 are just a few of the high-performance sensors that are included with the Sensor Tile (BlueNRG-M2). Each sensor has distinct abilities that help us comprehend the operating circumstances of the elevator as a whole.
- **Temperature Monitoring:** We can monitor temperature changes within crucial elevator components thanks to the STTS751 Digital Temperature Sensor's highly

accurate temperature measurements over a wide range. Even under difficult working conditions, its 16-bit temperature resolution enables accurate data collecting.

- **Motion Sensing:** The Sensor Tile can record exact acceleration data in several dimensions thanks to the LIS2DW12 and LIS3DHH 3-axis accelerometers. This function makes it easier to find elevator vibrations, movements, and other anomalies that could be signs of future problems.
- **Humidity Sensing:** With its precise and dependable humidity measurements, the HTS221 Humidity Sensor offers vital information for evaluating environmental conditions and potential moisture-related problems. It is perfect for inclusion into the Sensor Tile due to its small size and low power consumption.
- **Bluetooth Connectivity:** The integrated BlueNRG-M2 Bluetooth Application Processor enables wireless data transmission, allowing real-time communication and remote-control capabilities. The BLE stack's enhanced features, including improved data throughput and lower latency, facilitate seamless connectivity with other devices.

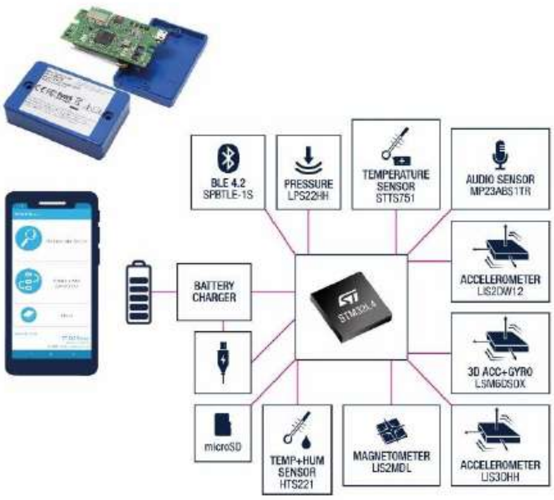


Figure VI: Sensor Tile Box

3.2.2 Digital Temperature Sensor (STTS751)

A vital part of the Sensor Tile, the Digital Temperature Sensor STTS751 is made to provide incredibly accurate and dependable temperature measurements for a variety of applications. This sensor is appropriate for monitoring settings with extreme temperature ranges thanks to its outstanding measuring range of -40°C to +125°C. Even under challenging operating conditions, it delivers accurate temperature readings with a range of 1.0°C from -10°C to +60°C.

With a precision of 0.0625°C and a 16-bit temperature resolution, the STTS751 can detect even minute temperature fluctuations. Applications needing accurate temperature monitoring, like environmental monitoring, industrial automation, and wearable medical devices, benefit particularly from this high-resolution capability.

The STTS751 makes use of the widely used I2C (2-wire) interface to provide simple communication with microcontrollers and other devices, facilitating smooth integration into a variety of systems. Additionally, it minimizes energy use due to its low power consumption, pulling only 45 A while in use, making it the perfect option for battery-powered devices and energy-conscious applications.

The STTS751's factory calibration eliminates the requirement for each calibration during deployment in addition to its technical competence. This feature guarantees correctness right out of the box and streamlines setup, freeing up critical time and resources for project development.

3.2.3 3-Axis Accelerometers (LIS2DW12 and LIS3DHH)

The LIS2DW12 and LIS3DHH 3-axis accelerometers, which are part of the Sensor Tile, are intended to record and analyze acceleration data in a variety of dimensions. These MEMS-based accelerometers are suited for a variety of motion-sensing applications because they have unmatched sensitivity and adaptability.

The user can select from a variety of measurement ranges offered by the LIS2DW12, including 2g, 4g, 8g, or 16g. We can adjust the accelerometer's sensitivity to meet the demands of our particular project thanks to its versatility. In order to ensure accurate and timely gathering of acceleration data, the sensor also provides customizable output data rates (ODR) of up to 1.6 kHz.

Similar to the LIS3DHH, which is appropriate for high-impact situations thanks to its broad measuring range and exceptional sensitivity. I2C and SPI interfaces are supported by both accelerometers, giving us the freedom to choose the best communication protocol for a seamless integration.

These accelerometers stand out for their exceptionally low power consumption, requiring just 50 A when in low-power mode. Furthermore, the availability of an inbuilt

FIFO (First In, First Out) buffer and multiple-interrupt capabilities improves the efficiency of data handling and lessens the strain on the main processor unit.

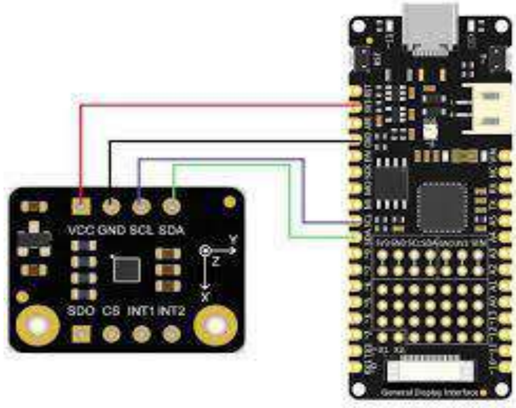


Figure VII: LIS2DW12 Sensor

3.2.4 Humidity Sensor (HTS221)

The inbuilt HTS221 humidity sensor in the Sensor Tile provides accurate and dependable measurements of relative humidity (RH) over a broad range of 0% to 100%. With an outstanding accuracy of 2% RH from 20% to 80% RH, this capacitive-based sensor ensures precise humidity readings.

The HTS221 offers temperature measuring between -40°C and +120°C in addition to humidity sensor. The reliability of environmental data acquisition is further increased by the temperature precision range of 15°C to 40°C of 0.5°C.

The HTS221 integrates easily into our data collecting system thanks to its I2C or SPI interfaces. It is an energy-efficient option for longer monitoring applications due to its low operating current of 2 A at an average 1 Hz output data rate, which ensures minimal power usage.

The sensor is suitable for our project because of its quick response time, factory calibration, and tiny form factor because accurate and real-time humidity and temperature data are crucial.

Figure VIII: HTS221 Sensor

3.2.5 Bluetooth Application Processor v5.2 (BlueNRG-M2)

An essential part of the Sensor Tile, the Bluetooth Application Processor v5.2, BlueNRG-M2 adds wireless communication to our data collecting system. It is an essential component of the Internet of Things (IoT) ecosystem since it is a Bluetooth Low Energy (BLE) application processor that enables seamless connectivity with other devices.

The BlueNRG-M2 supports Bluetooth version 5.2, which includes improved features like stronger security, lower latency, and better data speed. Applications needing continuous data transfer and communication are ideally suited for the BLE stack's strong and dependable connection. The BlueNRG-M2, which operates in the 2.4 GHz ISM band and enables effective wireless data transfer over short distances, is perfect for use in wearable technology, smart home technology, and industrial monitoring systems.

A hardware crypto accelerator is a feature of the application processor that improves data security during communication and guarantees the accuracy of the sent data. The integrated 256 KB flash memory also offers enough of room for firmware, configurations, and other important data storage.

The BlueNRG-M2 can smoothly interface with a variety of sensors and peripherals because to its numerous I/O possibilities. Additionally, it provides low-power modes to reduce energy usage and maximize battery life for battery-operated devices.

Our project now has a strong wireless communication interface thanks to the BlueNRG-incorporation M2's into the Sensor Tile, enabling real-time data transmission and remote control. Because of the increased flexibility and accessibility made possible by this, our data collecting system is more flexible and can be used for a wider range of applications.

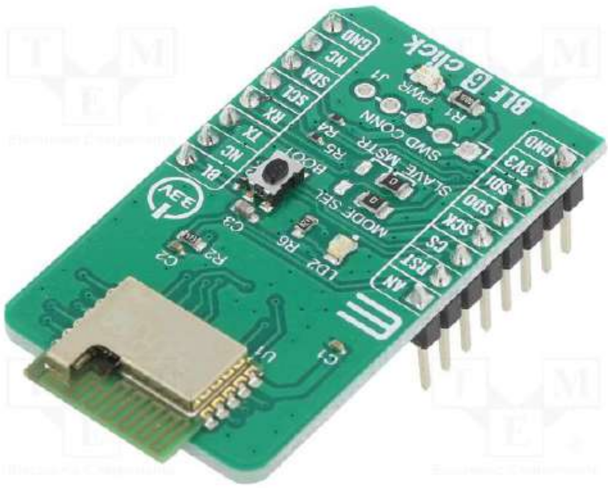


Figure IX: BlueNRG-M2

SOFTWARE TOOLS

The sophisticated software tools used to evaluate, interpret, and present the enormous amount of data provided by the Sensor Tile and other components are crucial to the success of our project. In this section, we go into greater detail on the software tools that we used in our project, emphasizing their importance and how they helped us accomplish our goals. The following is a list of the software utilized in the project:

- Query Language
- Python
- Grafana

3.3 Query Languages

In order to access and modify the time series data that was taken from the Sensor Tile and stored in CSV format, the Query Language (QL) plays a crucial role. Through structured and command-based searches, we can obtain data from databases and information systems using QL, a specialized computer programming language. Users can easily interact with and retrieve useful information from the host databases thanks to its querying constructs that are similar to those in English.

For the purposes of our project, we use QL to gain access to the time series data that will be used to train the Machine Learning (ML) models. However, the data passes through a number of crucial preprocessing processes before being fed into the ML models. Data purging, normalization, transformation, handling of missing information, feature engineering, and dealing with imbalanced data are some of these steps. These preprocessing procedures are necessary to guarantee the caliber and dependability of the data used to train the ML models, which in turn improves the precision and effectiveness of the algorithms for problem detection and health monitoring.

Additionally, query language aids in the ongoing history of vehicle data that we keep. Users are able to perform diagnostics and check the health status of their automobiles at any time thanks to the recorded data's CSV storage format. With the help of historical data, we can study trends over time and more easily spot patterns or possible problems that might not be obvious from just real-time data analysis.

3.4 Python

In our project, Python proves to be a strong and adaptable programming language, offering us a wide range of functions necessary for data processing, machine learning, and overall project development. Python is the perfect choice for Rapid Application Development due to its interpreted nature, object-oriented paradigm, and dynamic semantics (RAD). Additionally, its simple and legible syntax promotes code reuse and modularity through support for modules and packages, which lessens the complexity of program maintenance.

Python is the main programming language used in our project for data preparation, cleaning, and the training and testing of machine learning models. Our project is more efficient and effective as a result of its substantial standard library and broad ecosystem of third-party librariesPython gives us the ability to handle complex data operations with ease, which improves the precision and effectiveness of our defect detection and health monitoring systems.

Particularly, Pandas and NumPy, among other Python data processing packages, make it easier to manipulate and alter data. In order to prepare data for ML model training, these libraries offer robust capabilities for handling big datasets, handling missing values, and performing statistical calculations.

Additionally, Python's machine learning packages like Scikit-learn and TensorFlow enable us to quickly construct a variety of ML methods. These libraries can be used to create complex clustering, classification, and anomaly detection models, all of which are essential for spotting possible problems and keeping track of the health of vehicles.

3.5 Grafana

Grafana establishes itself as a potent and thorough visualization tool, converting unprocessed data into perceptive visualizations and dashboards. Its main objective is to organize and efficiently combine data, giving users the ability to understand complex measurements and trends through interactive queries and instructive visual representations.

Grafana's dashboard is essential to our project since it presents vehicle health information in a clear and user-friendly way. Grafana's graphical user interface (GUI) enables customers to get in-the-moment insights into a variety of aspects of their car's health. Critical metrics like temperature, acceleration, and humidity are clearly summarized in the dashboard, allowing for quick decisions and proactive action to solve any problems.

Grafana's flexibility and customization options allow us to tailor the dashboard to the specific needs of our project. By choosing the appropriate visualization types, such as line charts, bar graphs, and heatmaps, we can effectively represent complex data patterns and trends.

Additionally, we can configure real-time warnings for anomalous sensor readings or predetermined thresholds using Grafana's alerting features. By using a proactive approach, any irregularities or flaws are quickly brought to users' attention, enabling quick intervention and preventive steps.

By incorporating Grafana into our project, we improve the data's usability and accessibility, making it a crucial tool for tracking and diagnosing a vehicle's health. Users can receive deeper insights into the performance and health of their vehicles thanks to the user-friendly and educational dashboard developed with Grafana. This encourages data-driven decision-making, which eventually leads to safer and more effective transportation networks.

Chapter 4

PROJECT DESIGN AND IMPLEMENTATION

4.1 Overview

This chapter provides a thorough examination of the conception and implementation of our condition-based monitoring system for key engineering components, particularly elevator car doors. The methodology and guiding principles at each stage, from data collection to front-end development, will be described.

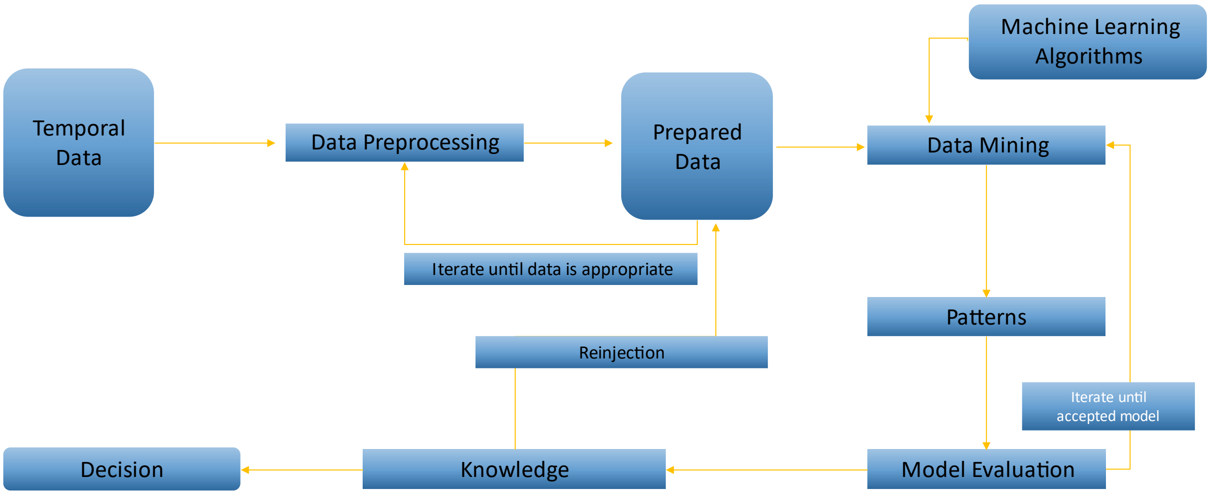


Figure X: Project Design Overview

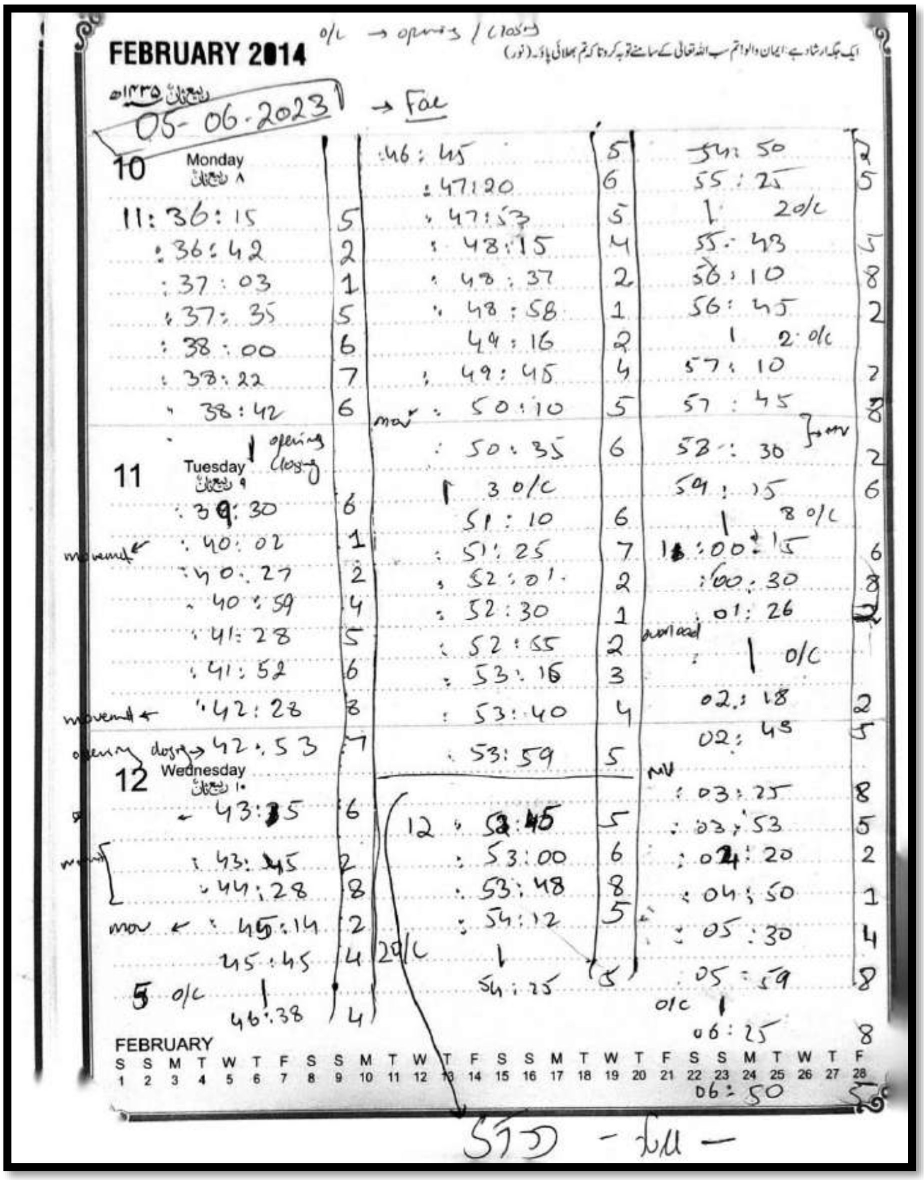
4.2 Data Acquisition

4.2.1 Sensor Configuration

The sensor Tile box, which has temperature and humidity sensors in addition to accelerometers to monitor XYZ axis vibrations, was used to collect the data.We selected this specific configuration due to its capability of providing rich and relevant information on the state of the elevators without invasive procedures.

4.2.2 Data Collection Method

A combination of automated data collection and manual logging was utilized. The data was acquired from both faculty and student elevators at different periods, with attention given to instances such as door opening, closing, and stuck scenarios. The choice of these elevators provided a diverse and realistic dataset representative of the real-world scenarios we intended to monitor.



4.3 Data Preprocessing

4.3.1 Missing Values Handling

Given that the missing values were negligible, we chose to remove them to maintain the authenticity of the data. The reasoning behind this was to prevent potential biases introduced through imputation or estimation methods.

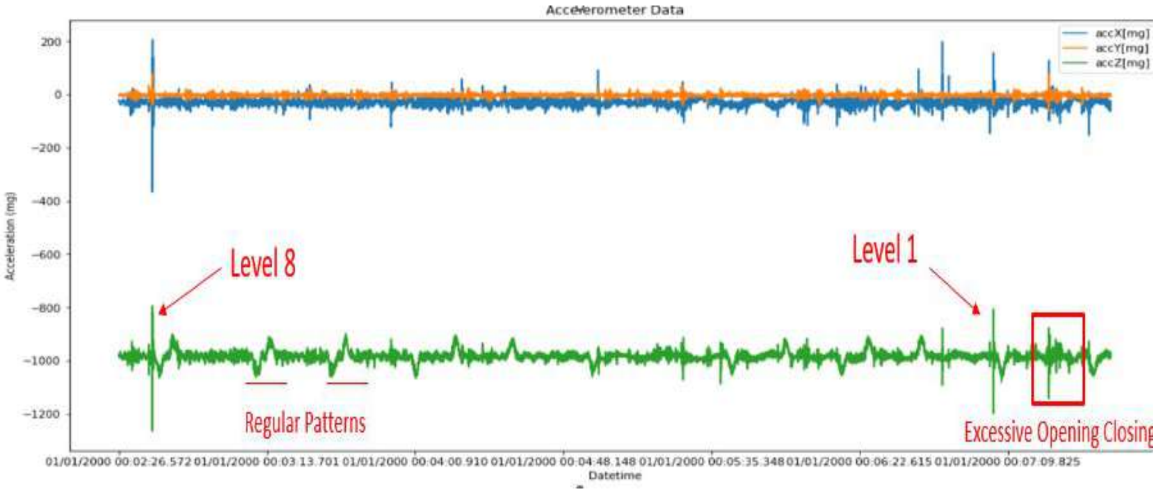
4.3.2 Integration of Data

Data from different time intervals and sensors were meticulously merged into a consistent and continuous dataset. This integration was crucial for enabling comprehensive analysis and ensuring that the integrity of the temporal relationships between data points was preserved.

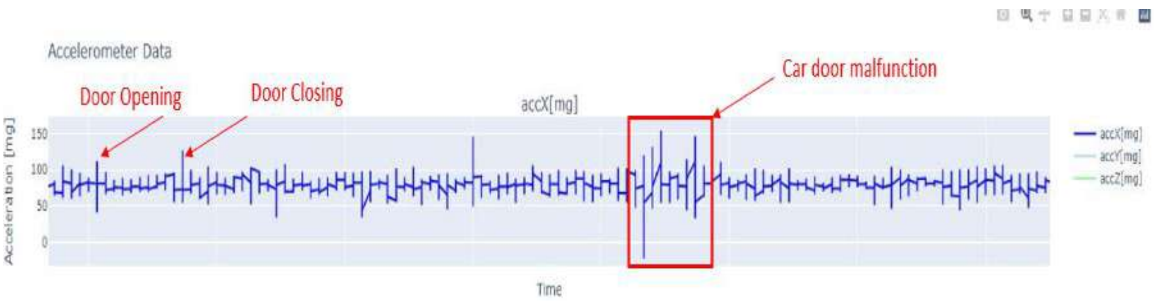
4.4 Data Analysis and Pattern Recognition

4.4.1 Identification of Patterns and Understanding Faults

Through initial intuitive analysis, certain regular patterns and peaks were observed in the data.



These patterns initially seemed ambiguous but were clarified through meticulous monitoring and manual logging.

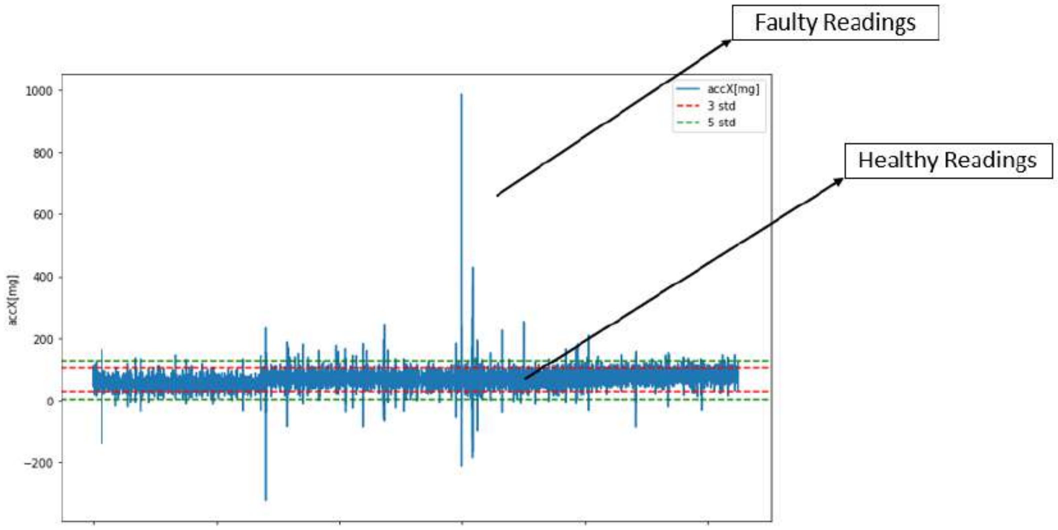


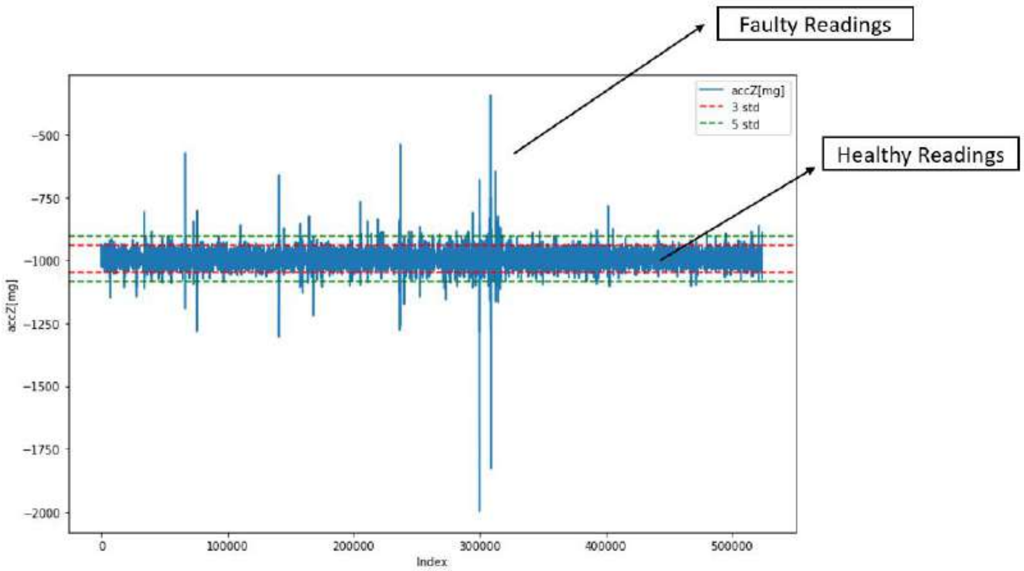
The detailed analysis revealed:

Peaks in Data: The peaks corresponded to instances of car door opening and closing. Initially, these spikes in the readings might have been misinterpreted, but by synchronizing the data with real-time observations, we were able to associate these peaks with normal operational behaviors.

Regular Excessive Patterns: More concerning were the regular but excessive patterns in the data. These were ultimately identified as indications of car door malfunctions. By cross-referencing these patterns with the manually maintained log and the real-world observations, we were able to isolate and understand these anomalies.

Utilizing Standard Deviation: To systematically categorize the data, standard deviation values for the XYZ axis were utilized. This statistical measure provided a quantitative method to distinguish between healthy and faulty states, supporting intuitive insights with a robust mathematical foundation.





The manual log, in conjunction with statistical tools, provided a nuanced understanding of the data patterns. This combined approach ensured that the observed data was not only analyzed in a mathematical context but also validated against actual physical behaviors of the elevators. It demonstrated the importance of domain knowledge and real-world observation in enhancing the data analysis, ultimately leading to a more accurate and reliable fault detection system.

4.4.2 Thresholding

Thresholding on temperature and humidity readings was put in place to keep an eye on environmental factors that could cause mechanical problems. To make sure the thresholds were pertinent and sensitive to the particular conditions being investigated, they were derived from domain expertise and empirical study.

4.5 Model Selection and Training

4.5.1 Model Comparison

We explored various classification models, such as SVM, Decision Trees, Random Forest, and XGBoost. After rigorous testing and validation, XGBoost was selected. This choice was driven by its proven efficiency in handling large datasets and its ability to provide a balanced bias-variance tradeoff.

4.5.2 Error Coding

Specific error codes were designed for different fault conditions. This coding was developed after intensive collaboration with domain experts to translate complex sensor data into meaningful and actionable fault descriptions. The conditional statements applied for coding are grounded in practical understanding and technical knowledge of elevator mechanics.

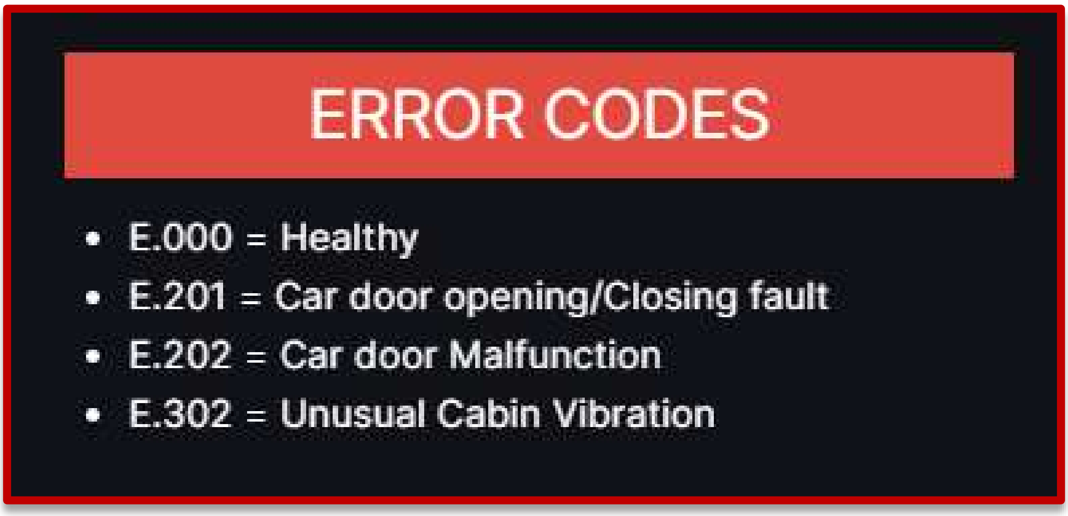


Figure XI: Error Codes

4.6 Back-End Development

4.6.1 Real-Time Data Processing and Streaming

The raw sensor data was not only stored but was also actively analyzed in real-time using the trained machine learning model. This dual-action process entailed the following:

- **Real-Time Classification:** The model, leveraging algorithms like XGBoost, was applied to the incoming data stream to classify the elevator's state into various categories (e.g., healthy, car door opening/closing faults, etc.). This classification was done on-the-fly, without storing the data first, allowing for immediate action if necessary.
- **Streaming to InfluxDB:** The classified data, along with the raw sensor readings (XYZ, temperature, humidity), were then streamed into InfluxDB. They were organized into points and buckets to maintain chronological ordering and facilitate efficient querying.

4.6.2 Data Organization in InfluxDB

- **Points:** Each classified data record, or point, contained the actual sensor readings and the model's classification, along with relevant metadata such as the timestamp, elevator ID, etc.
- **Buckets:** The points were stored in designated buckets according to their type or relevance. This organization made segmented analysis and querying easier, which improved the system's effectiveness.

4.6.3 Querying and Analysis

- **Complex Queries:** Relevant queries were used to filter, aggregate, and transform the data in InfluxDB, enabling both historical analysis and real-time monitoring.

Figure XII: Complex Queries

- **Fault Detection and Pattern Recognition:** The discovery of particular fault patterns, trends, and maybe predictive insights was made possible by the real-time categorization in conjunction with past data analysis.

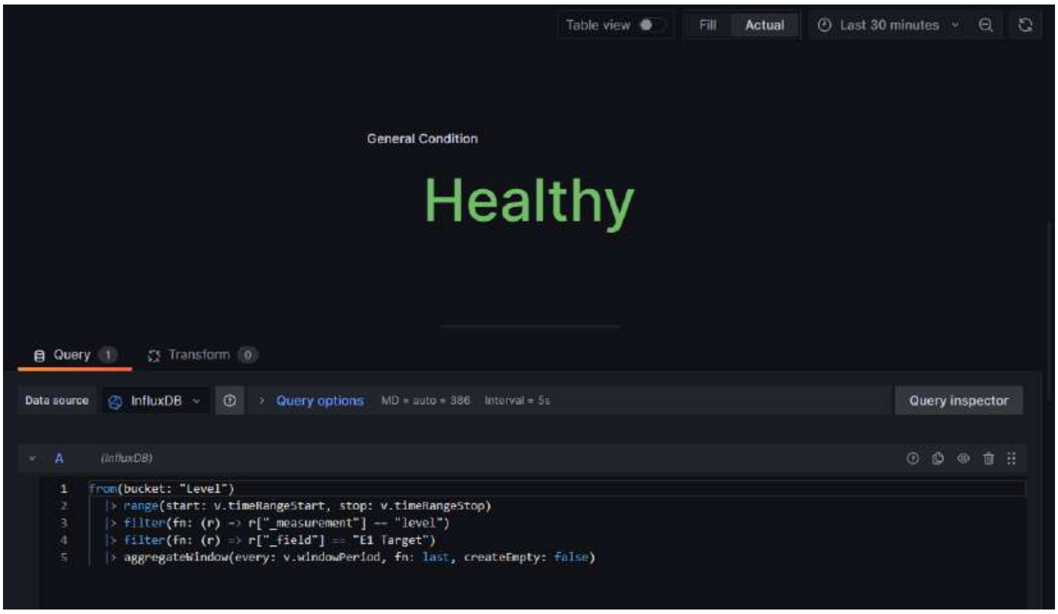


Figure XIII: Fault Detection Query

4.6.4 Integration with Front-End

The HMI panels created in Grafana were driven by the real-time classified data and insights from queries. A dynamic and interactive front-end interface reflecting the current state of the elevators was made possible by this seamless connectivity, which also allowed the ability to notify the necessary stakeholders as necessary.

4.7 Front-End Development (HMI)

4.7.1 Overview of HMI Design

Grafana, a popular open-source platform for monitoring and observability, was chosen for the human-machine interface (HMI). It gave us the chance to create intuitive panels that made it possible for users of all technical and non-technical backgrounds to interact with the information and insights produced by the monitoring system. Two connected panels made up the design:

4.7.1.1 Panel 1: General Overview of Elevators

The first panel gave a general, live rundown of both elevators. It had the following components:

- **Elevator Floor:** The current floor of each elevator was indicated via an easily understood visual depiction. Without needing to decipher raw data, it enabled users to comprehend the geographical positioning and movement pattern of the elevators.

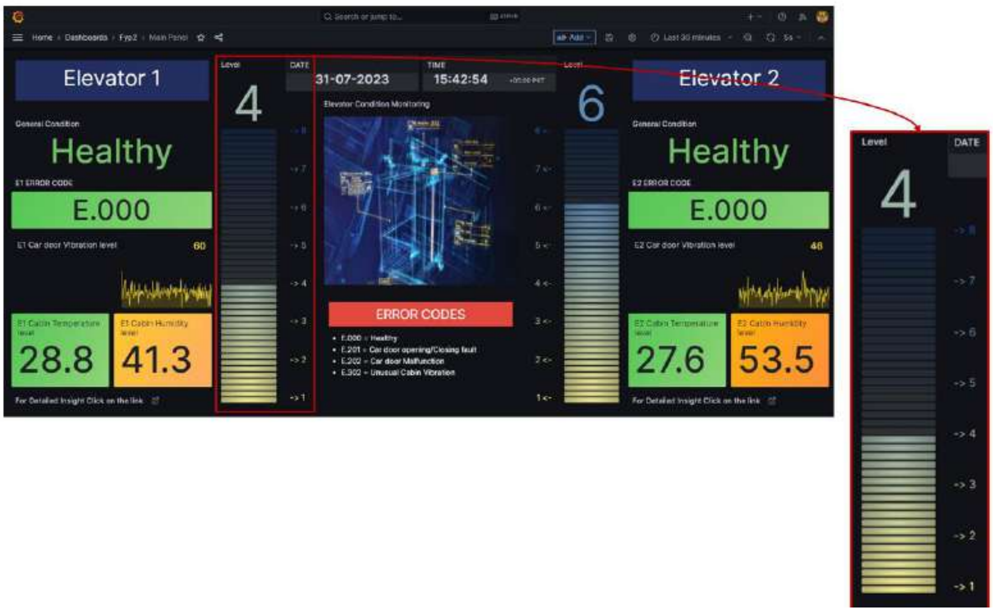


Figure XIV: Elevator Levels

- **General Condition:** A color-coded health status was included for quick recognition of the overall condition of each elevator (Healthy/Faulty). This immediate feedback enabled swift response when an issue was detected.

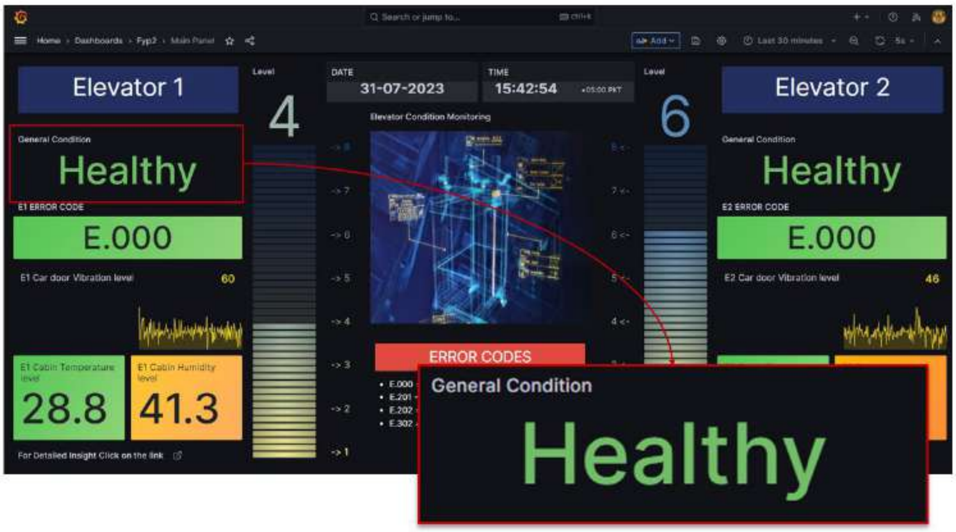


Figure XV: General Condition

- **Error Codes:** Specific error codes were presented to classify the state of the elevators. These included E.000 for healthy, E.201 for car door opening/closing faults, E.202 for car door malfunction, and E.302 for unusual cabin vibration. These codes were designed to offer a standardized and concise way to understand complex mechanical states.

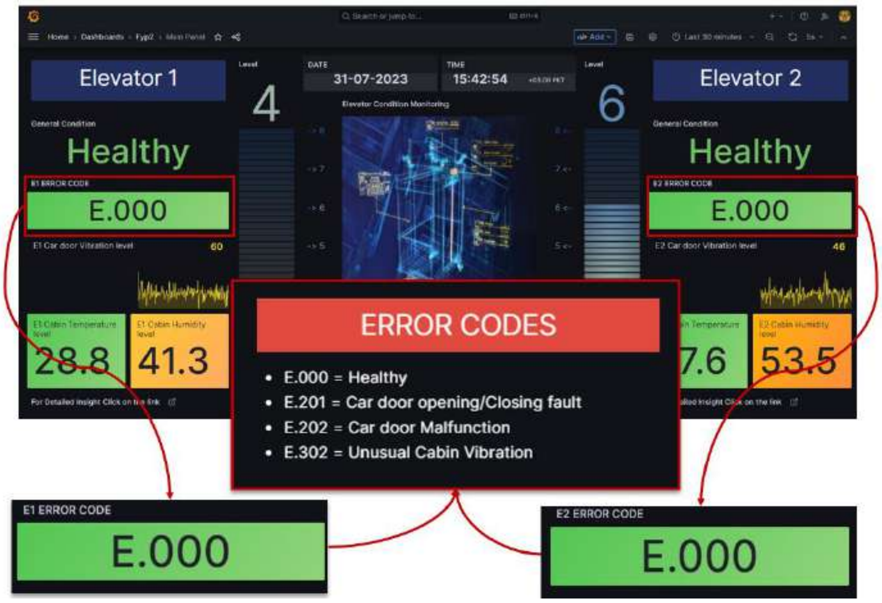


Figure XVI: Error

4.7.1.2 Panel 2: Detailed Insights

The second panel, which provided comprehensive information about each elevator separately, was activated by pressing a button in the first panel. This panel, which comprised the following, was created to assist more knowledgeable users who needed in-depth information.

- **Alert List:** Specific warnings for problems found inside the elevators were delivered through a dynamically updated list of alerts. It enabled maintenance staff to order their jobs according to importance and address the most pressing problems first.

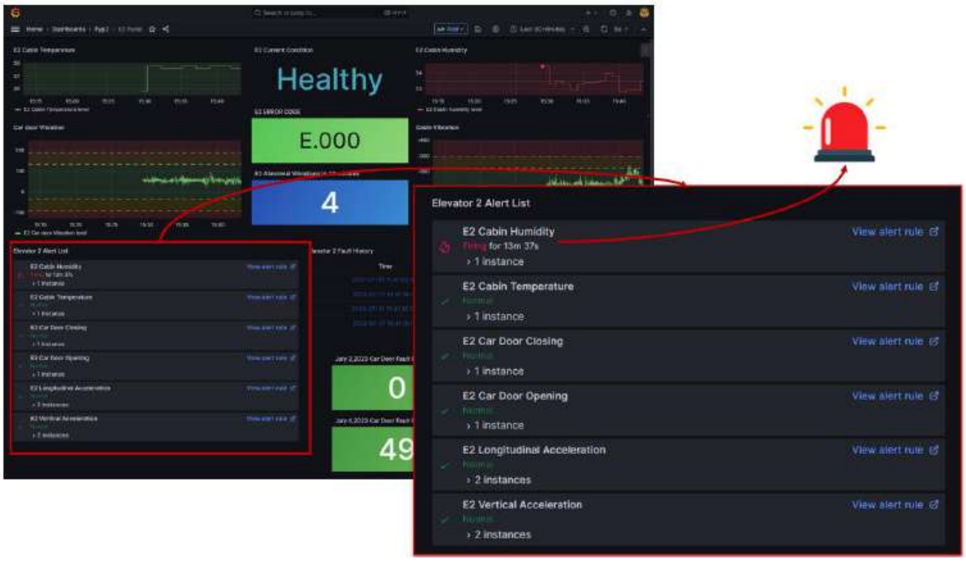


Figure XVII: Alert

- **Fault History:** A timeline of all reported faults was presented in this section. It supported preventative maintenance plans, made it easier to spot potential underlying problems, and allowed for the comprehension of repeating trends.

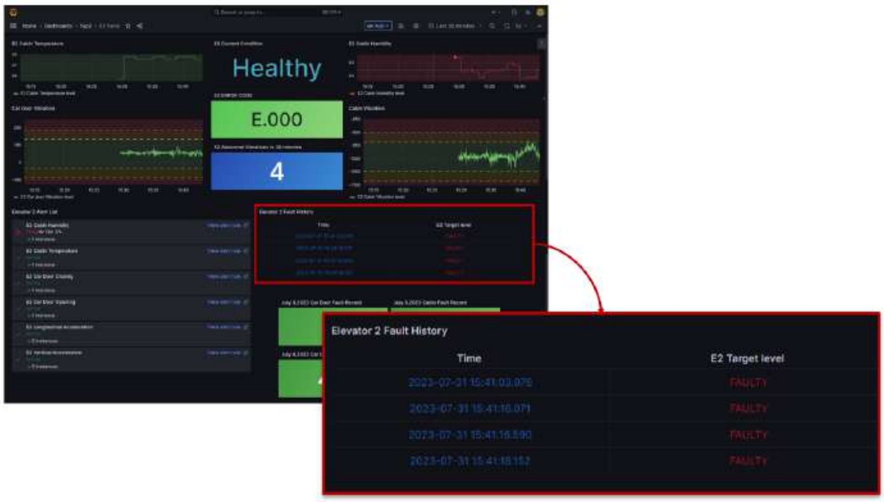


Figure XVIII: Fault History

- **Count of Abnormal Vibrations:** A specialized visualization showed the count of abnormal vibrations in the last 30 minutes. This offered an immediate snapshot of unusual activities, particularly related to the car door vibration pattern, that might indicate potential issues.

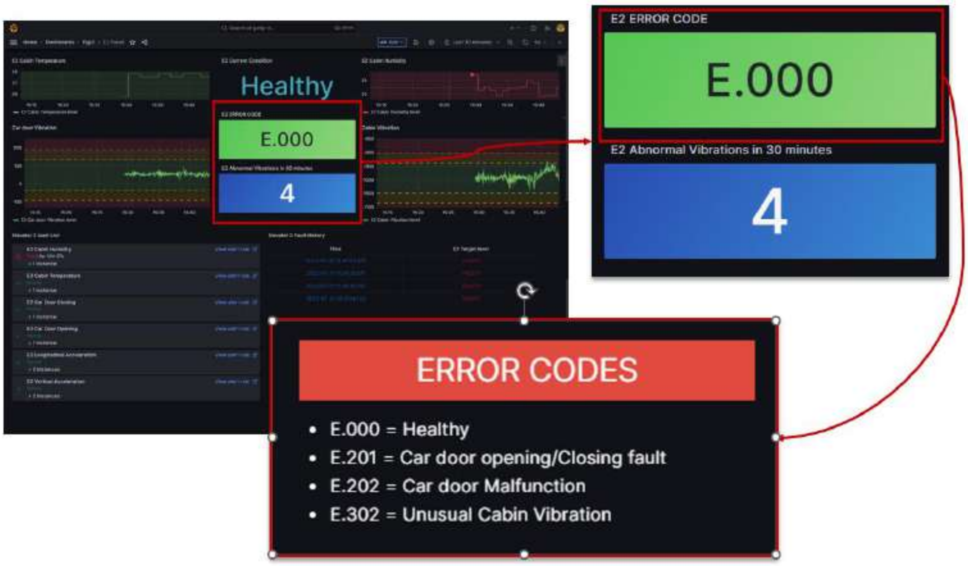


Figure XIX: Count of Abnormal Vibration

- **Car Door and Cabin Vibration Pattern:** A graph or other visual representation could be used to depict the car door and Cabin vibration pattern. It allowed for a deep analysis of the elevator doors' mechanical behavior, assisting in pinpointing specific issues or inefficiencies.

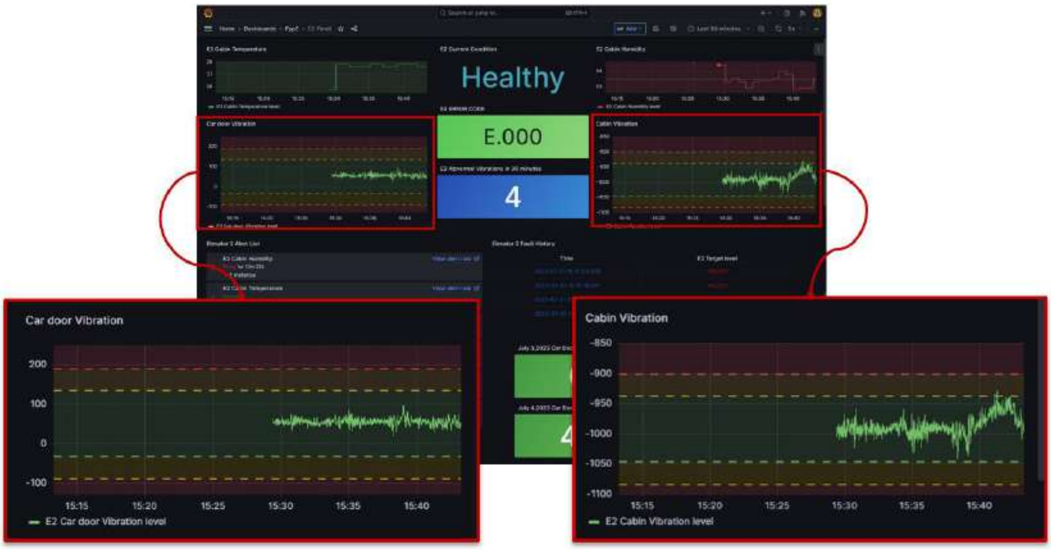


Figure XX: Vibration Patterns

4.7.2 Interactivity and User Experience

The link between the two panels was designed to facilitate a smooth and logical transition from a general understanding to a more detailed analysis. The button-driven interactivity ensured that users could navigate between views effortlessly, accommodating both casual observation and detailed investigation.

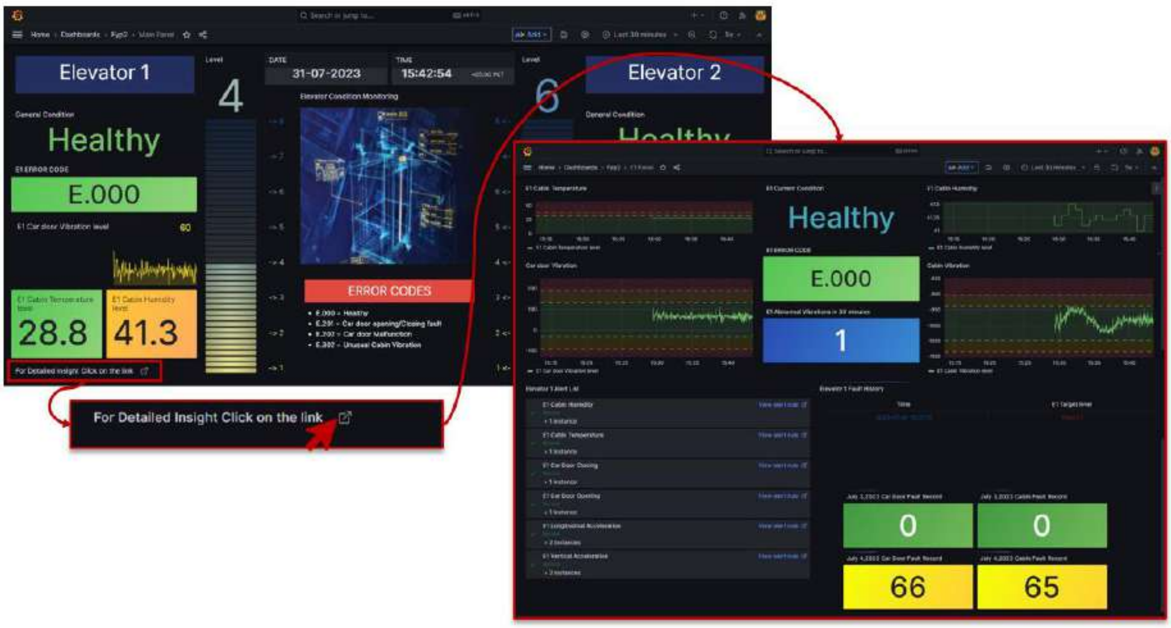


Figure XXI: Interactivity and User Experience

4.7.3 Design Rationale

The HMI design aimed to translate complex engineering and statistical insights into intuitive and actionable information. The choice of Grafana, along with the specific design elements in the panels, was motivated by the need for accessibility, clarity, and relevance. By offering two levels of insight, the system could cater to a wide range of users, from facility managers to technical experts, ensuring that all stakeholders had the information they needed in a form that was meaningful to them.

4.8 Summary

This chapter has provided a comprehensive insight into the project's design and implementation. Through carefully crafted methodologies, rigorous analysis, collaborative efforts, and user-centered design, the project successfully realized its goal of monitoring and diagnosing critical engineering assets.

Chapter 5

PROJECT RESULTS

This chapter elucidates the results stemming from the development of a prototype designed to monitor the condition of critical engineering assets in elevators, with a focus on car doors. Utilizing dummy data, the prototype represents a critical foundational step towards a real-world solution.

5.1 Data Acquisition Results

5.1.1 Custom Data Collection Mechanism

The development of a tailored data collection process using a senorTile box allowed the simulation of real-world accelerometer, temperature, and humidity readings. This innovation overcame challenges related to unavailable datasets and provided insights into the potential for real-world implementation.

5.1.2 Data Integrity and Quality

The completeness and minimal missing values of the simulated data were maintained meticulously, offering a meaningful representation of potential real-world conditions.

5.1.3 Considerations for Actual Sensors

The prototype’s data acquisition process requires further adaptation to actual built-in elevator sensors, acknowledging the complexity and uniqueness of real-world sensor data.

5.2 Prototype Analysis and Pattern Identification

5.2.1 Identification of Fault Problems

The analysis process led to the successful discovery of patterns, such as peaks corresponding to car door opening and closing, as well as regular excessive patterns indicative of car door malfunction.

5.2.2 Classification based on Standard Deviation

By employing standard deviation values for the XYZ axis, the project established a viable method for classifying healthy and faulty conditions within the simulated environment.

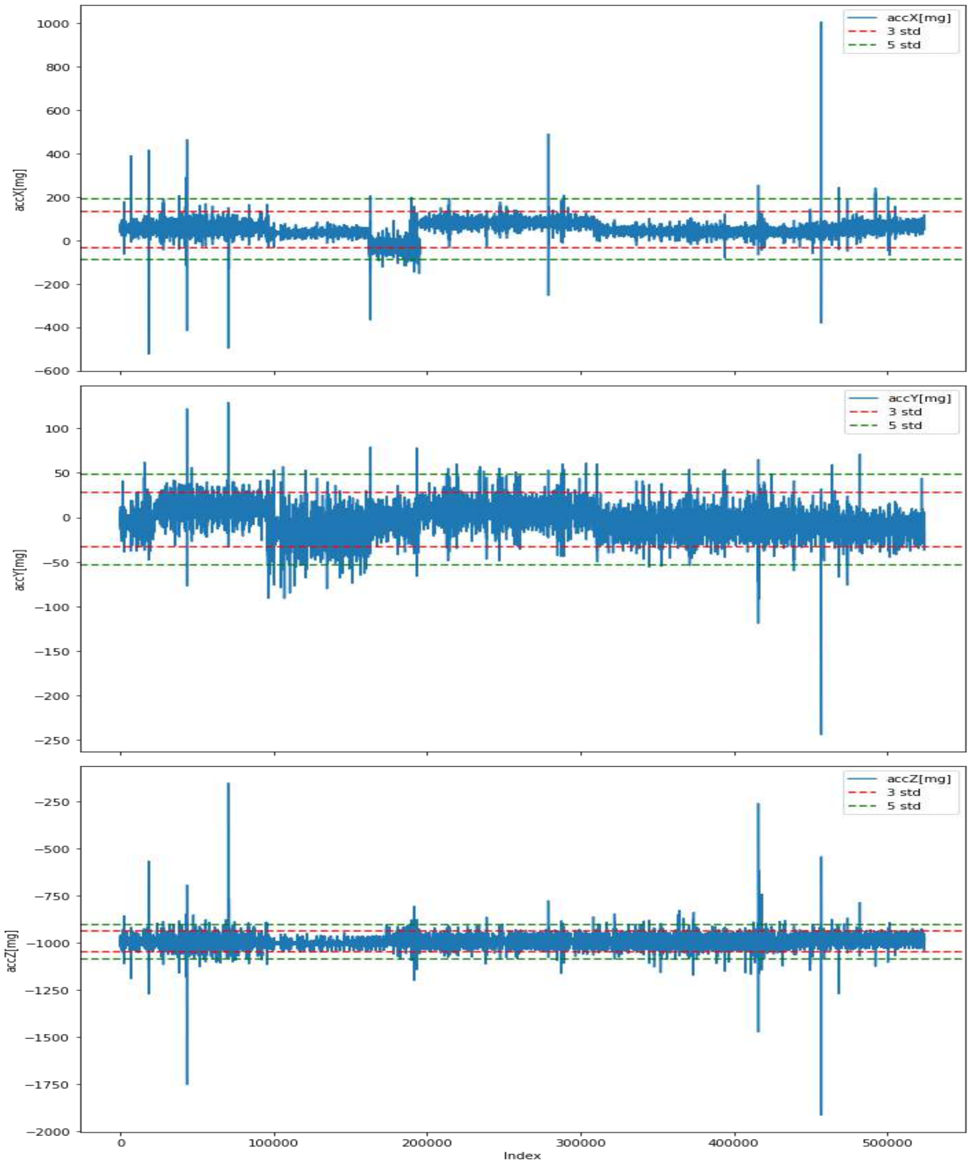


Figure XXII: Standard Deviation Classification

5.2.3 Real World Considerations

Future stages will necessitate a comprehensive validation process with actual sensor data, ensuring the translation of insights gained from the prototype to a real-world context.

5.3 Machine Learning Model Training and Validation

5.3.1 Selection and Performance of XGBoost

The XGBoost model was chosen following the training of several classifiers. The prototype's higher performance serves as a yardstick for its use in real-time problem detection.

The Receiver Operating Characteristic curve (ROC curve) is a graphical representation of a binary classification model's performance at different classification thresholds. As a single metric to assess the effectiveness of the model, the AUC (Area Under the Curve) is a scalar value that represents the area under the ROC curve. Our model's ROC Curve looks like this:

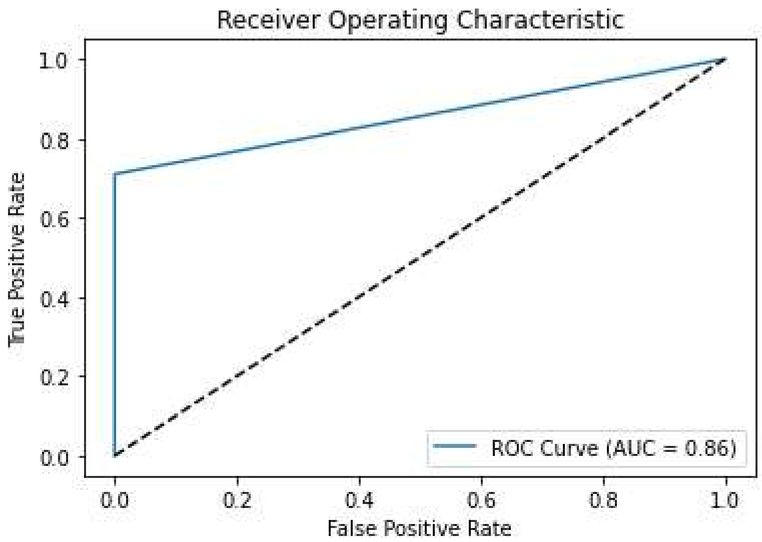


Figure XXIII: ROC Curve

With an AUC score of 0.86, the xgboost model has a respectable level of discriminating power, or the ability to tell the positive from the negative classes. The model's capacity to differentiate between the two classes is improved by a higher AUC value.

5.3.2 Implications for Real Time Analysis

The success in real-time classification underscores the feasibility of integrating machine learning into industrial applications, requiring further testing and optimization with actual data. We export the model and then perform prediction on the real time data coming from the sensors.

5.4 Back End Development and Data Streaming

5.4.1 Influx DB Integration

InfluxDB served as the back-end, facilitating the streaming of data in the form of points and buckets. This successful integration of simulated data demonstrates the system's readiness to adapt to real-world data streams.

5.4.2 Future Scaling and Optimization

Additional considerations for scalability, performance optimization, and security need to be addressed in subsequent phases to ensure robustness in real-world scenarios.

5.5 Human Machine Interface Design

5.5.1 Two Panel Interface in Grafana

The design and development of a two-panel interface in Grafana provided both general overviews and detailed insights, successfully offering a user-centric experience.
Following are the reflections of the Human machine interface built in Grafana for this project:

Figure XXIV: Main Panel of Dashboard

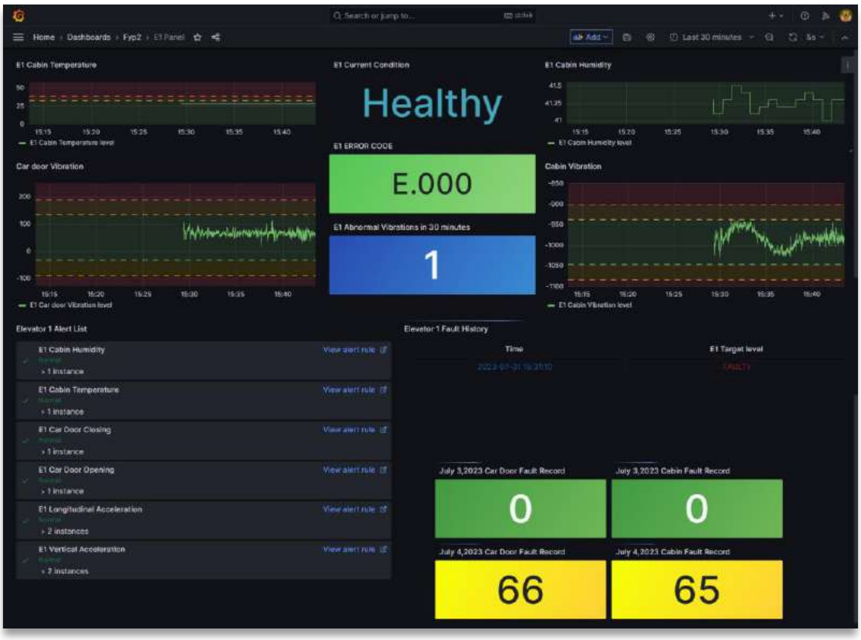


Figure XXV: Elevator 1 Insight Panel

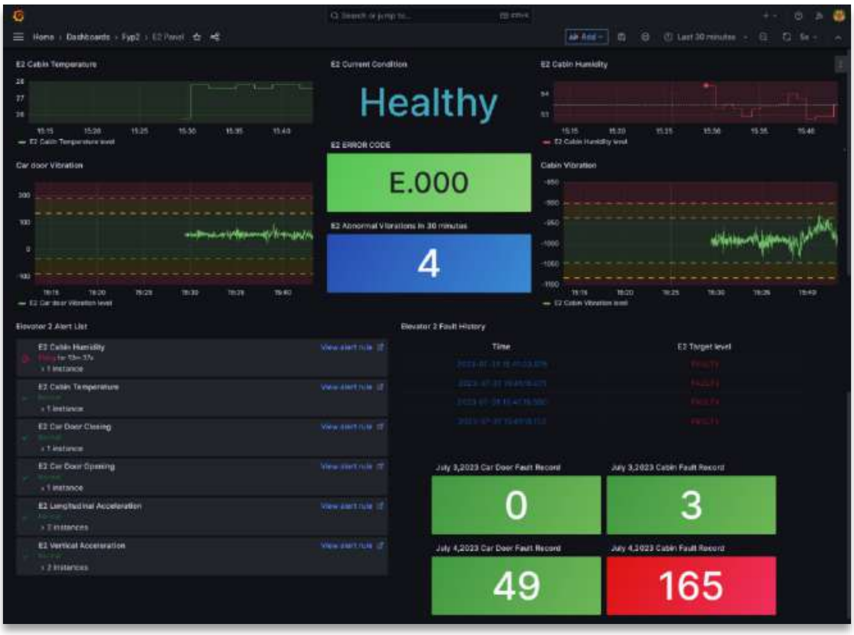


Figure XXVI: Elevator 2 Insight Panel

5.5.2 Transition to Real World Applications

The transition to a real-world setting may require further refinement and customization to align with specific user needs and existing elevator monitoring systems.

5.6 Concluding Remarks

The prototype's success in translating simulated data into actionable insights, real-time fault detection, and intuitive monitoring lays a strong foundation for future endeavors in condition-based monitoring. The project highlights both the opportunities and challenges of applying advanced data analytics in the field of engineering.

Recognizing that this is a simulated environment, the next stages will require intensive collaboration with industry partners, adaptation to real-world sensor systems, and further validation and optimization. The robustness, scalability, and security of the entire system will be paramount in the transition from the prototype to a commercial solution.

This chapter has underscored the significance of this project, not only in terms of technological innovation but also in its potential to revolutionize safety and efficiency within elevator operations.

Chapter 6

PROJECT CONCLUSION

The condition-based monitoring of critical engineering assets using Machine Learning (ML) has been a challenging yet fulfilling endeavor, with the focus on elevator car doors serving as a case study. This final chapter serves to encapsulate the key milestones, challenges, and learnings from this project.

6.1 Project Overview

This project has succeeded in implementing a real-time monitoring system for elevators, utilizing sensor data from accelerometers and environmental sensors. It has also effectively integrated the use of ML algorithms, specifically XGBoost, to classify various fault conditions. By streaming this data into InfluxDB and utilizing Grafana for Human-Machine Interface (HMI), a comprehensive end-to-end solution was achieved.

6.2 Challenges Faced

- **Data Acquisition:** The absence of available datasets necessitated the collection of raw data from university elevators. This not only consumed significant time and resources but also required meticulous planning to ensure data quality and relevance.
- **Pattern Identification and Labeling:** The identification of patterns related to specific faults was a labor-intensive process. Cross-referencing data with manually maintained logs and then labeling it for training the model proved to be a time-consuming task.

- **Integration Complexity:** Integrating various components such as sensors, databases, and ML models presented a multifaceted challenge. Ensuring seamless communication between these elements required careful consideration and continuous refinement.
- **Model Tuning and Validation:** Achieving the desired accuracy and robustness in the classification model required extensive experimentation and fine-tuning. This involved a rigorous process of testing different algorithms, features, and hyperparameters.
- **Real-time Processing Requirements:** Implementing a real-time processing pipeline to handle continuous data streaming and classification posed technological and logistical challenges. It required optimization at multiple levels to ensure efficiency and reliability.

6.3 Achievements and Contributions

6.3.1 Custom Data Collection Framework

The development of a custom data collection framework using senorTile box represents a major achievement in the project. This involved:

- **Tailored Sensor Deployment:** By selecting accelerometers, temperature, and humidity sensors specifically for the task, the project ensured that the data collected was highly relevant to the faults being studied.
- **Data Integration and Preprocessing:** Combining raw data from different sensors, handling missing values, and integrating data collected at different intervals presented unique challenges. Overcoming these challenges allowed for a robust and seamless dataset that was integral to the project's success.
- **On-Site Implementation:** The real-world deployment of sensors within the university's elevators ensured the authenticity of data and provided invaluable insights into the actual operating conditions of the engineering asset.
- **Benchmark for Future Research:** The methodologies developed for data collection and preprocessing can serve as a reference for future researchers working on similar asset-monitoring projects.

6.3.2 Real Time Fault Detection and Monitoring

The implementation of real-time fault detection and monitoring for elevator doors has multiple facets:

- **Dynamic Classification Model:** Utilizing the XGBoost model, the system was capable of classifying data in real-time, thus providing immediate insights into the health of the elevators.
- **Diverse Fault Detection:** The system was fine-tuned to detect various specific faults, including car door opening and closing malfunctions. This granularity in fault detection is pivotal for early intervention and preventive maintenance.
- **Enhanced Safety Measures:** By enabling prompt fault detection, the system enhances the safety of elevator operations, minimizing risks and potential downtimes.
- **Contribution to Operational Efficiency:** The efficiency of maintenance and repair operations can be significantly improved by timely alerts, thus saving both time and resources for the operating entity.

6.3.3 Comprehensive HMI Design

The creation of a comprehensive Human-Machine Interface (HMI) using Grafana provided several key benefits:

- **Simple Overview Panels:** The dual-panel layout made it easy for stakeholders to rapidly grasp the general state of the elevators and then, if necessary, to delve into more specific details.
- **Real-time Alert System:** The fault history and alert list offered a method for continuous monitoring that could promptly alert users to problems as they arose.
- **Custom Error Codes and Visualization:** The HMI provided a sophisticated understanding of various fault circumstances by incorporating specific error codes and car door vibration patterns.
- **User-Friendly Approach:** The design considered the requirements and preferences of various stakeholders, including building managers, maintenance staff, and safety authorities. By doing this, it was made sure that the information was not only accurate but also usable and actionable.
- **Linkage to System in the Real World:** Setting a benchmark for similar condition based monitoring system after integrating with real world elevator systems

6.4 Future Directions and Implications

The project's successful demonstration of real-time fault detection for elevator car doors opens up several promising avenues for future exploration and potential impact.

- **Adaptation to Other Engineering Assets:** The methodologies and frameworks developed can be adapted and extended to other critical engineering assets like turbines, engines, or industrial machinery. By applying similar pattern recognition and machine learning techniques, other industries can benefit from predictive maintenance and fault detection.
- **Enhanced Data Analytics and Prediction Models:** Future work could focus on implementing more advanced data analytics techniques and deep learning models. These may provide higher accuracy and even predict faults before they occur, thus evolving the system from mere detection to prediction.
- **Integration with IoT and Smart Infrastructure:** The system can be incorporated into Internet of Things (IoT) networks and smart infrastructure, thereby enhancing the connectivity and intelligence of urban environments. Such integration would enable a more comprehensive view of asset health across an entire city or industrial complex.
- **Commercialization and Scalability:** Exploring commercial applications and partnerships with elevator manufacturers or maintenance providers could lead to the development of a scalable product. The alignment of the system with industry standards and regulations would be key in this phase.
- **Sustainability Considerations:** The energy efficiency and sustainability of the system itself could be a focus of future research. This involves optimizing the energy consumption of the sensors and computing infrastructure.

6.5 Final Reflection

The journey of this project has been a blend of innovation, perseverance, and learning. It has transcended mere academic pursuit and provides insights into the real-world application of emerging technologies.

- **Interdisciplinary Collaboration:** The project underscores the importance of interdisciplinary collaboration, as it melds engineering, data science, software development, and human-computer interaction.
- **Learning from Challenges:** The challenges faced have become valuable lessons in project management, problem-solving, and resilience. They shaped not just the final outcome but also the broader understanding of how theory translates into practice.

- **Ethical Considerations and Safety Compliance:** Consideration of ethical issues, such as privacy in data collection and safety compliance in real-time monitoring, have provided insights into the broader societal implications of technology deployment.
- **Contribution to Academic and Industrial Knowledge:** Beyond its immediate applications, the project adds to the growing body of knowledge in condition-based monitoring and intelligent asset management. It contributes both to academic research and provides tangible solutions that may influence industry practices.
- **Personal and Professional Growth:** On a personal level, the project has been a catalyst for growth, fostering technical acumen, project management skills, and a nuanced understanding of the convergence of technology and societal needs.

In sum, the project has transcended the boundaries of a typical academic endeavor, uncovering a myriad of opportunities and learnings. Its innovative integration of machine learning, real-time data processing, and user-centric design not only holds promise for future technological advancements but also stands as a testament to the transformative power of interdisciplinary research.

REFERENCES

A. A. a. A. Abdelhadi. (2022). Condition-Based Monitoring and Maintenance: State of the Art Review.

Jia, X. G. (2021). Elevator Running Fault Monitoring Method Based on Vibration Signal.

L. G. Dapeng Niu. (2021). Preventive maintenance period decision for elevator parts based on multi-objective optimization method,.

Liu, J. W. (2018). Research on Preventive Maintenance Strategy of Elevator Equipment.

Niu, D. (2021). Preventive maintenance period decision for elevator parts based on multi-objective optimization method.

Pink, A. P. (n.d.). *Machine Learning Model For Predictive Maintenance Of Lifts/Elevators*. Retrieved from https://aisingapore.org/tech-offers/machine-learning-model-for-predictive-maintenance-of-lifts-elevators/

R. B. F. a. E. A. Edirisinghe. (2016). "Decision Making for Predictive Maintenance in Asset Information Management. *researchgate.net*.

Shen, L. J. (2021). Predictive maintenance on an elevator system using machine learning.

Sun, X. A. (2022). Elevator Leveling Failures Monitoring Device and Method. *hindawi.com*.

Verma, G. (2021). Implementing Deep Learning Model to Predict the Maintenance of an Elevaor System.

APPENDICES

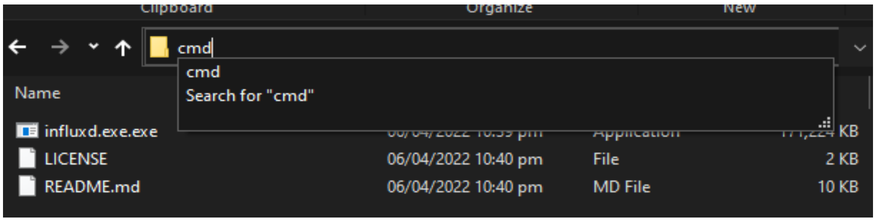
The pre-requisites of implementing the below given steps are:

- Data should be collected and stored in a .csv file.
- DB, Python (along with required libraries) and Grafana should be pre-installed.

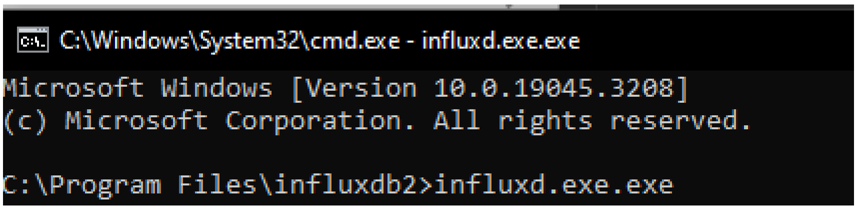
Implementation Steps:

Step by Step implementation of project are given below:

1. Open command prompt on the specified folder where influxdb setup is placed.



2. Launch Influx DB using command prompt



3. Open Google Chrome and search http://localhost:8086/.

4. Run the following script to send data to db

```
import influxdb_client
import os
import pandas as pd
from influxdb_client import InfluxDBClient, Point, WritePrecision
from influxdb_client.client.write_api import SYNCHRONOUS
from datetime import datetime
from time import sleep
import xgboost as xgb

token =
"BP95o5wBElej3umupMw8ftm3nekbXJG2jKinZaJVBhJ5_XmvyIFXNwcqmVtp3qVbij4xQ89cFCyVktA3V
8eybg=="
org = "FYP"
```

```
bucket = "Level"
bucket1 = "record"
url="http://localhost:8086"

model = xgb.Booster()
model.load_model("model_file.model")

write_client = influxdb_client.InfluxDBClient(url=url, token=token, org=org)
write_api = write_client.write_api(write_options=SYNCHRONOUS)

# Read data from CSV using pandas
csv_file = "Data_finalize_versions/Final_elevator_F+S.csv"
df = pd.read_csv(csv_file)

record = "Data_finalize_versions/Data_record.csv"
record_df = pd.read_csv(record, parse_dates=["dd/mm/yyyy"])



# Iterate over rows and send data to InfluxDB
for _, row in record_df.iterrows():

    day1_x = float(row[1])
    day1_y = float(row[2])
    day1_z = float(row[3])

    day1_x1 = float(row[4])
    day1_y1 = float(row[5])
    day1_z1 = float(row[6])

    day2_x = float(row[7])
    day2_y = float(row[8])
    day2_z = float(row[9])

    day2_x1 = float(row[10])
    day2_y1 = float(row[11])
    day2_z1 = float(row[12])

    day3_x = float(row[13])
    day3_y = float(row[14])
    day3_z = float(row[15])

    day3_x1 = float(row[16])
    day3_y1 = float(row[17])
    day3_z1 = float(row[18])
```

```
day4_x = float(row[19])
day4_y = float(row[20])
day4_z = float(row[21])

day4_x1 = float(row[22])
day4_y1 = float(row[23])
day4_z1 = float(row[24])

day5_x = float(row[25])
day5_y = float(row[26])
day5_z = float(row[27])

day5_x1 = float(row[28])
day5_y1 = float(row[29])
day5_z1 = float(row[30])

day6_x = float(row[31])
day6_y = float(row[32])
day6_z = float(row[33])

day6_x1 = float(row[34])
day6_y1 = float(row[35])
day6_z1 = float(row[36])


# Set current timestamp
timestamp = datetime.now()
unix_time = int(timestamp.timestamp() * 1000)

# Convert timestamp to ISO 8601 format
time_string = timestamp.isoformat()

# Create Point
point = (
  Point("record")
  .tag("loc", "record")
  .time(unix_time, write_precision=WritePrecision.MS)
  .field("day1_x", day1_x)
  .field("day1_y", day1_y)
  .field("day1_z", day1_z)
  .field("day1_x1", day1_x1)
  .field("day1_y1", day1_y1)
  .field("day1_z1", day1_z1)
  .field("day2_x", day2_x)
  .field("day2_y", day2_y)
```

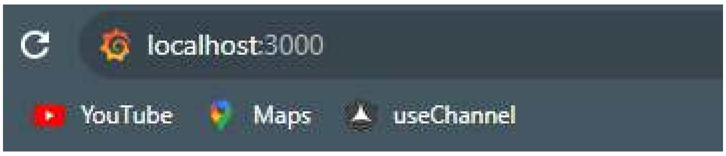
```
        .field("day2_z", day2_z)
        .field("day2_x1", day2_x1)
        .field("day2_y1", day2_y1)
        .field("day2_z1", day2_z1)
        .field("day3_x", day3_x)
        .field("day3_y", day3_y)
        .field("day3_z", day3_z)
        .field("day3_x1", day3_x1)
        .field("day3_y1", day3_y1)
        .field("day3_z1", day3_z1)
        .field("day4_x", day4_x)
        .field("day4_y", day4_y)
        .field("day4_z", day4_z)
        .field("day4_x1", day4_x1)
        .field("day4_y1", day4_y1)
        .field("day4_z1", day4_z1)
        .field("day5_x", day5_x)
        .field("day5_y", day5_y)
        .field("day5_z", day5_z)
        .field("day5_x1", day5_x1)
        .field("day5_y1", day5_y1)
        .field("day5_z1", day5_z1)
        .field("day6_x", day6_x)
        .field("day6_y", day6_y)
        .field("day6_z", day6_z)
        .field("day6_x1", day6_x1)
        .field("day6_y1", day6_y1)
        .field("day6_z1", day6_z1)
    )


    # Write data to InfluxDB
    write_api.write(bucket=bucket, org=org, record=point)

    #sleep(0.5)
write_client.close()



# Iterate over rows and send data to InfluxDB
for _, row in df.iterrows():

    acceleration_x = float(row[2])
    acceleration_y = float(row[3])
    acceleration_z = float(row[4])
    temperature = float(row[5])
```

```
humidity = float(row[6])
level = int(row[7])
X_fault = float(row[8])
Y_fault = float(row[9])
Z_fault = float(row[10])
fault = int(row[11])
#Target = int(row[13])

# Use the loaded XGBoost model for prediction
data = xgb.DMatrix(pd.DataFrame({
    "acceleration_x": [acceleration_x],
    "acceleration_y": [acceleration_y],
    "acceleration_z": [acceleration_z]
}))
# Target = int(model.predict(data)[0])
predictions = model.predict(data)
Target = int(predictions[0] >= 0.5)

acceleration_x1 = float(row[16])
acceleration_y1 = float(row[17])
acceleration_z1 = float(row[18])
temperature1 = float(row[19])
humidity1 = float(row[20])
level1 = int(row[21])
X_fault1 = float(row[22])
Y_fault1 = float(row[23])
Z_fault1 = float(row[24])
fault1 = int(row[25])
#Target1 = int(row[27])

# Use the loaded XGBoost model for prediction
data1 = xgb.DMatrix(pd.DataFrame({
    "acceleration_x": [acceleration_x1],
    "acceleration_y": [acceleration_y1],
    "acceleration_z": [acceleration_z1]
}))
#Target1 = int(model.predict(data1)[0])
predictions1 = model.predict(data1)
Target1 = int(predictions1[0] >= 0.5)



# Set current timestamp
timestamp = datetime.now()
unix_time = int(timestamp.timestamp() * 1000)
```

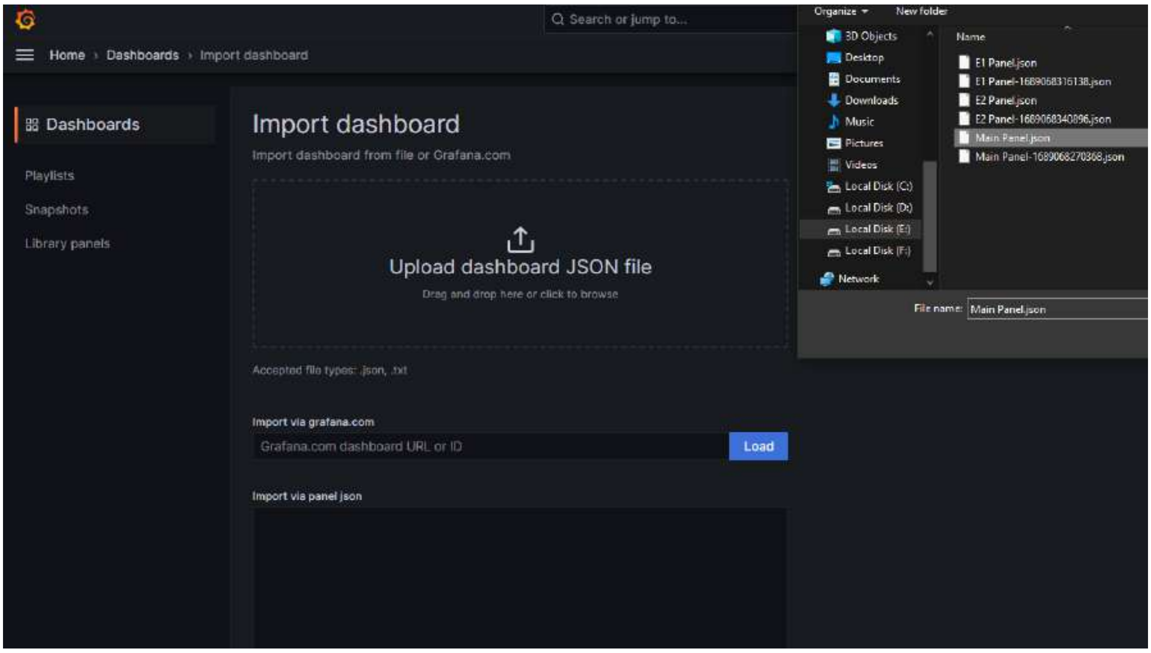
```
        # Convert timestamp to ISO 8601 format
        time_string = timestamp.isoformat()

        # Create Point
        point = (
            Point("level")
            .tag("loc", "level")
            .time(unix_time, write_precision=WritePrecision.MS)
            .field("E1 Car door Vibration", acceleration_x)
            .field("E1 Rail Acceleration", acceleration_y)
            .field("E1 Cabin Vibration", acceleration_z)
            .field("E1 Cabin Temperature", temperature)
            .field("E1 Cabin Humidity", humidity)
            .field("E1 Level", level)
            .field("E1 Target", Target)
            .field("E1 Car Door Fault", X_fault)
            .field("E1 Leveling Fault", Y_fault)
            .field("E1 Alignment Fault", Z_fault)
            .field("E1 fault", fault)


            .field("E2 Car door Vibration", acceleration_x1)
            .field("E2 Rail Acceleration", acceleration_y1)
            .field("E2 Cabin Vibration", acceleration_z1)
            .field("E2 Cabin Temperature", temperature1)
            .field("E2 Cabin Humidity", humidity1)
            .field("E2 Car Door Fault", X_fault1)
            .field("E2 Leveling Fault", Y_fault1)
            .field("E2 Alignment Fault", Z_fault1)
            .field("E2 Error Code", fault1)
            .field("E2 Level", level1)
            .field("E2 Target", Target1)
        )

        # Write data to InfluxDB
        write_api.write(bucket=bucket, org=org, record=point)

        sleep(0.5)

    #write_client.close()
```

5. Data will start loading to database and queries are automatically get active.

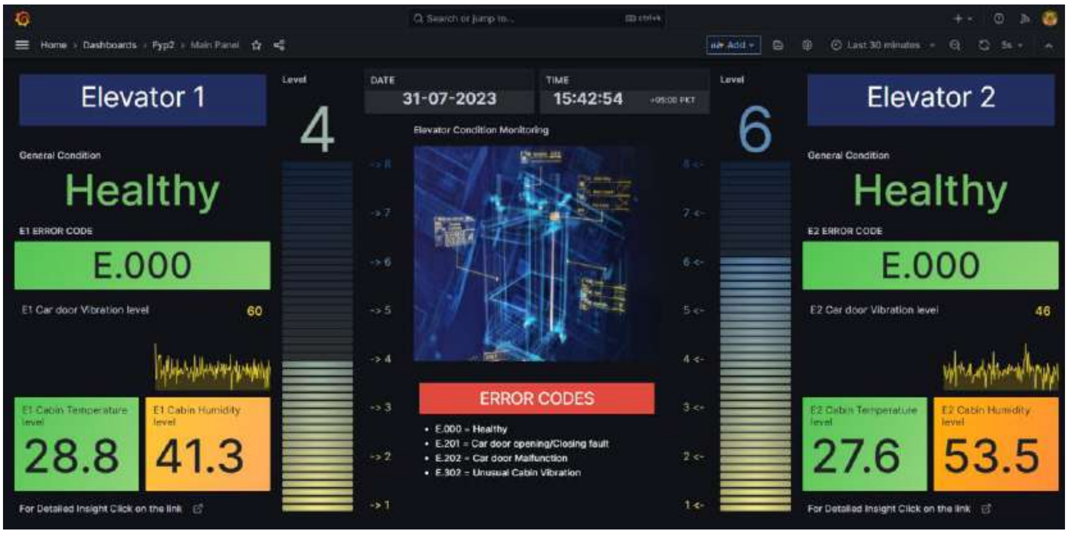
6. Go to Google Chrome and open Grafana by searching this localhost.

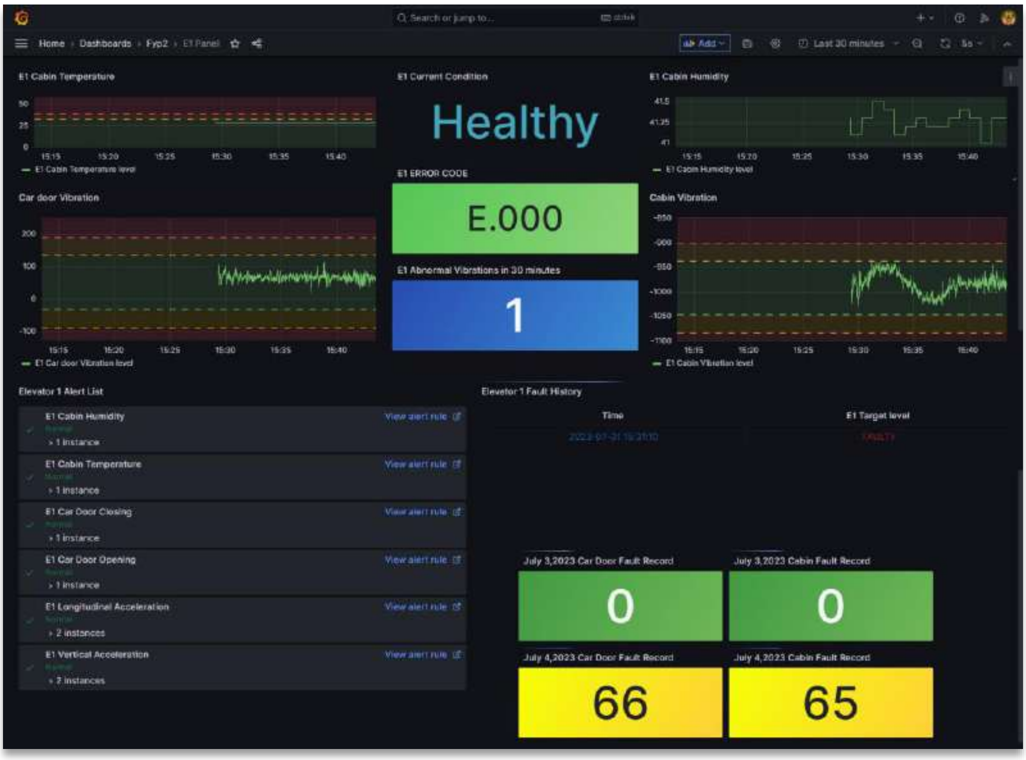


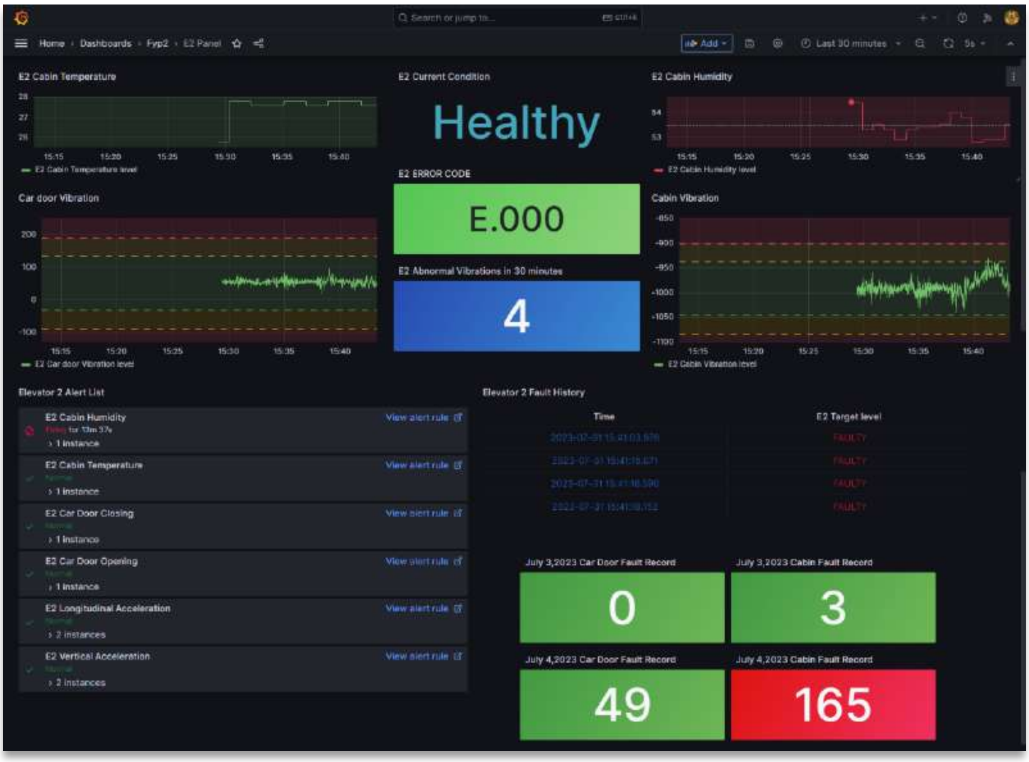
7. Then upload the json files of Dashboard into it and run them.



8. Now you can view the dashboards.




Home › Dashboards › Fyp2 › E1 Panel
Last 30 minutes
E1 Cabin Temperature
E1 Current Condition
Healthy
E1 Cabin Humidity
E1 ERROR CODE
E.000
Car door Vibration
E1 Abnormal Vibrations in 30 minutes
1
Cabin Vibration
Elevator 1 Alert List
Elevator 1 Fault History
Time
E1 Target level
E1 Cabin Humidity
E1 Cabin Temperature
E1 Car Door Closing
E1 Car Door Opening
E1 Longitudinal Acceleration
E1 Vertical Acceleration
View alert rule
July 3,2023 Car Door Fault Record
0
July 3,2023 Cabin Fault Record
0
July 4,2023 Car Door Fault Record
66
July 4,2023 Cabin Fault Record
65


Home › Dashboards › Fyp2 › E2 Panel
Last 30 minutes
E2 Cabin Temperature
E2 Current Condition
Healthy
E2 Cabin Humidity
E2 ERROR CODE
E.000
Car door Vibration
E2 Abnormal Vibrations in 30 minutes
4
Cabin Vibration
Elevator 2 Alert List
Elevator 2 Fault History
Time
E2 Target level
E2 Cabin Humidity
E2 Cabin Temperature
E2 Car Door Closing
E2 Car Door Opening
E2 Longitudinal Acceleration
E2 Vertical Acceleration
View alert rule
July 3,2023 Car Door Fault Record
0
July 3,2023 Cabin Fault Record
3
July 4,2023 Car Door Fault Record
49
July 4,2023 Cabin Fault Record
165

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