UNDERGRADUATE FINAL YEAR PROJECT REPORT

Department of Computer and Information Systems Engineering

NED University of Engineering and Technology

ENHANCING INDUSTRIAL EFFICIENCY WITH PREDICTIVE MAINTENANCE AND ANALYTICS FOR INDUCTION MOTOR

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Author’s Declaration

We declare that we are the sole authors of this project. It is the actual copy of the project that was accepted by our advisor(s) including any necessary revisions. We also grant NED University of Engineering and Technology permission to reproduce and distribute electronic or paper copies of this project.

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Statement of Contributions

- *FARAH HUSSAIN*, contributed to the project by designing wireframes and did prototyping activities for the dashboard interface.
- *MALAIKA ALI*, developed the frontend of the dashboard, ensuring its functionality.
- *SYED MUHAMMAD*, contributed in API development, and database management.
- *GORVE KUMAR*, contributed to the project by gathering the CWRU dataset and by handling data.
- All team members actively participated in documenting project's proposal meeting minutes, doing literature review, compiling mid-year reports, and delivering presentations, ensuring effective communication and transparency throughout the project.

Executive Summary

The industrial sector relies heavily on the efficient operation of machinery, with motors playing a critical role in various manufacturing processes. Induction motors, in particular, constitute around 90% of industrial processes, making their proper maintenance crucial for uninterrupted production. Neglecting maintenance can lead to increased power consumption, overall production downtime, and economic losses. To address this, we propose a specialized Predictive Maintenance (PdM) solution for industrial motors. Our project's core objective is to develop a predictive maintenance solution utilizing vibration signatures and machine learning algorithms to identify faults. Our main goal is to develop a user-friendly dashboard which will provide real-time status updates and detailed performance reports highlighting the deviations and anomalies in motor performance, along with an automated notification system to alert the maintenance teams of impending potential failures, enabling proactive preventive actions. The React JS is chosen for development for its component-based architecture, simplifying development by breaking down UIs into reusable modules. Its virtual DOM enhances performance, ensuring fast rendering of dynamic content. This approach emphasizes economic efficiency and sustainability in industrial motor operation with an effective and proactive maintenance system.

Acknowledgments

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List of Abbreviations

PdM	Predictive Maintenance
API	Application Programming Interface
ML	Machine Learning
DL	Deep Learning
UI	User Interface
DOM	Document Object Model
CNN	Convolutional Neural Network
LSTM	Long Short-term Memory
CWRU	Case Western Reserve University

United Nations Sustainable Development Goals

The Sustainable Development Goals (SDGs) are the blueprint to achieve a better and more sustainable future for all. They address the global challenges we face, including poverty, inequality, climate change, environmental degradation, peace and justice. There is a total of 17 SDGs as mentioned below.

- ☐ No Poverty
- ☐ Zero Hunger
- ☐ Good Health and Well being
- ☐ Quality Education
- ☐ Gender Equality
- ☐ Clean Water and Sanitation
- ☐ Affordable and Clean Energy
- ☒ Decent Work and Economic Growth
- ☒ Industry, Innovation and Infrastructure
- ☐ Reduced Inequalities
- ☐ Sustainable Cities and Communities
- ☐ Responsible Consumption and Production
- ☐ Climate Action
- ☐ Life Below Water
- ☐ Life on Land
- ☐ Peace and Justice and Strong Institutions
- ☒ Partnerships to Achieve the Goals

Chapter 1 Introduction

1.1. Background Information

The diagnostic analysis of faults in induction motors holds paramount importance in ensuring the continuous operation of industrial processes. Predictive maintenance (PdM) systems enable the proactive identification of equipment faults prior to their occurrence, decreasing unplanned downtime and lowering maintenance costs. They do this by utilizing advanced data analytics and sensor technology. The implementation of a PdM solution for industrial motor monitoring is the main goal of this project. The dashboard acts as the main interface for viewing data on motor performance that is gathered in real time from multiple sensors. With the help of ReactJs, a JavaScript package well-known for its component-based architecture and effective rendering, the dashboard gives maintenance personnel an overview of motor health and makes it easier to identify abnormalities or possible problems in a timely manner.

1.2. Significance and Motivation

PdM plays a crucial role in modern industrial settings by offering a proactive approach to equipment maintenance and management. The importance of PdM lies in its ability to enhance operational efficiency, reduce downtime, and optimize maintenance schedules. [1]

PdM helps in identifying potential equipment failures before they occur, allowing for proactive maintenance actions to be taken. This approach reduces unplanned downtime, minimizes repair costs, and extends the lifespan of assets, resulting in significant cost savings for organizations.

Regular monitoring and maintenance of equipment through PdM practices contribute to a safer working environment by reducing the risk of sudden equipment failures that could pose safety hazards to personnel. PdM enables maintenance activities to be scheduled based on actual equipment condition rather than fixed time intervals. This approach helps in optimizing maintenance schedules, reducing unnecessary maintenance tasks, and maximizing the utilization of resources.

PdM relies on data collected from sensors and monitoring devices to assess the health of equipment. This data-driven approach allows for informed decision-making regarding maintenance strategies, resource allocation, and equipment replacement, leading to more effective and efficient operations. Organizations that implement PdM practices gain a competitive edge by minimizing downtime, improving asset performance, and reducing maintenance costs. This can result in increased customer satisfaction, higher product quality, and improved overall competitiveness in the market. [2]

1.3. Aims and Objectives

The project's core objective is the development of a specialized predictive maintenance solution for industrial motors, employing vibration signatures and machine learning algorithms to identify faults. A user-friendly dashboard will be developed to provide real-time status updates and detailed performance reports for all monitored motors. An automated alert system will notify maintenance teams in advance of potential motor failures, enabling proactive preventive actions. This approach underscores the project's commitment to ensuring the efficient and reliable operation of industrial motors emphasizing economic efficiency and sustainability.

1.4. Methodology

In recent years, there has been a growing interest in building advanced techniques for fault diagnosis in the context of bearing fault diagnosis. Older approaches involve applying predetermined signal transformations, such as empirical mode decomposition and fast Fourier transform, to convert time-series signals into frequency domain representations. However, these methods are often time-consuming. Diagnostic outcomes may be influenced by the limitations of large datasets and subjective human analysis.

To address these challenges, this project proposes an approach that utilizes an automatic feature learning neural network, which directly processes raw vibration signals as inputs. This framework employs convolutional neural networks (CNNs) with varying kernel sizes to automatically extract distinct frequency signal characteristics from the raw data. Also, bi-directional CNN-Bi-LSTM networks are utilized to classify fault types based on the learned features. Preprocessing techniques, such as down-sampling, are applied to effectively reduce the number of parameters involved. Experimental results demonstrate the efficacy of this approach.

1.5. Report Outline

This report provides a comprehensive exploration of predictive maintenance (PdM) solutions for industrial motors. In the introduction chapter, the critical role of industrial motors and the challenges associated with their maintenance is discussed, highlighting the potential of PdM in addressing these challenges. Literature review is thoroughly discussed in Chapter 2, highlighting the significance of PdM in optimizing operational efficiency and cost reduction, with a specific focus on utilization of vibration signal analysis and machine learning methodologies. Chapter 3 outlines the methodology employed in developing a predictive maintenance dashboard, emphasizing user-centric design and the integration of frontend and backend technologies. Chapter 4 presents the results of the project, showcasing the functionality of dashboard views designed for different user roles. Chapter 5 concludes by summarizing the key findings and evaluating the project's contributions to the field of industrial PdM.

Chapter 2 Literature Review

2.1. Introduction

The industrial sector relies heavily on the efficient operation of machinery, with motors playing a critical role in various manufacturing and production processes. Induction motors are the backbone of the industry, with approximately 90% of industrial processes heavily dependent on their functionality. [3]

PdM software is developed to identify impending maintenance requirements and schedule tasks during optimal timeframes for minimizing costs. This data collecting and system tracking also help you make smart decisions at the real time. [4]

Every year, it is estimated that U.S. industry spends $200 billion on the maintenance of plant equipment and facilities and the result of ineffective maintenance leads to a loss of around more than $60 billion [5]. PdM can save you around 10-40% on maintenance costs [6].

Author in [3] reported, based on a report by PwC, the implementation of PdM in the manufacturing sector has the potential to enhance uptime by 9%, lower costs by 12%, mitigate safety, health, environmental, and quality risks by 14%, and extend the lifespan of aging assets by 20%.

By leveraging predictive analytics and real-time sensor data, the proposed methodology enables accurate predictions of motor or machine states with high precision, leading to improved equipment reliability, and enhanced operational efficiency in industrial settings.

2.2. Vibrational Signal Analysis

Vibration signals and stator currents are commonly used monitoring signals in fault diagnosis approaches for induction motors. Vibration signals can provide valuable information about the mechanical condition of the motor, such as bearing faults, unbalance, and misalignment, while stator currents can indicate electrical faults like broken rotor bars or short-circuits [2]. Vibration signals are preferred over stator currents in scenarios where early detection of mechanical faults is paramount, and unexpected downtime can have significant financial implications. They are favored in environments with high levels of electrical noise or unstable power supplies, where stator currents may be unreliable or difficult to interpret accurately [7].

Integrating vibration signal analysis into predictive maintenance strategies enables proactive maintenance planning and helps optimize the reliability and performance of industrial motor systems [8].

While measured stator currents can also offer valuable information about the electrical performance of machines, they may not capture the subtle mechanical issues that vibration signals can reveal. Therefore, the use of vibration signal analysis as a predictive maintenance tool is favored for its effectiveness in detecting a wide range of mechanical faults and abnormalities in industrial equipment. [1]

2.3. Dataset and ML Models

The data used in [12] study are from Case Western Reserve University (CWRU) and were collected from a mechanical system driven by a motor under four different loads, with a sampling frequency of 48 kHz. The dataset includes normal conditions and faults such as outer race fault (OF), inner race fault (IF), and roller fault (RF) with fault diameters of 0.18 mm, 0.36 mm, and 0.54 mm, respectively.

In [9] the motor bearing dataset provided by the CWRU was used to test the proposed CNN-based fault diagnosis method. The dataset contains ten health conditions with nine fault conditions and one normal condition. Three fault types are roller fault (RF), outer race fault (OF), and inner race fault (IF), and each fault type has three different damage sizes. The proposed method achieved a prediction accuracy of 99.79% on this dataset, demonstrating its effectiveness in diagnosing faults in motor bearings.

The author in [10] used the dataset that includes vibration signals measured by two accelerometers placed at the fan-end (FE) and drive-end (DE) of the motor. The signals are digitized at a sampling frequency of 12 kHz and include different types of bearing conditions, including healthy bearings and bearings with various fault sizes. The ML model used in the paper is a Deep Neural Network (DNN) with a wide structure and integration of feature fusion as a network layer. The accuracies of the different ML models used in the paper are as follows: Alexnet with DE sensor: Achieved 100% accuracy under the 0 hp load condition and high accuracies under other load conditions. Lenet5 with DE sensor: Achieved accuracies ranging from 35.89% to 86.22% under different load conditions. PCA-based fusion: Achieved accuracies ranging from 53.88% to 86.37% under different load conditions. DS-based fusion: Achieved accuracies ranging from 54.42% to 86.24% under different load conditions. Proposed method (DNN-based fusion): Achieved accuracies ranging from 65.11% to 99.11% under different load conditions.

2.4. Dashboard

A dashboard is the controlling interface for keeping industrial motors running smoothly. It gives maintenance teams a real-time view of how the motors are doing by pulling in data from different sensors. Comprehensible charts and graphs, facilitates the timely identification of anomalous patterns or indicators of potential issues. This mitigate serious problems that shut down production. Utilizing functions such as customizable alerts and analysis of past data enables us to effectively manage maintenance duties and ensure the smooth operation of the motors [11].

Chapter 3 Methodology

3.1. Introduction

The methodology employed in this project involves a systematic approach to address the development of a predictive maintenance dashboard for industrial motors. This chapter outlines the steps taken from requirements gathering to the implementation of the backend infrastructure. The project primarily focuses on catering to the needs of three user roles, the administrator, factory in-charge, and floor in-charge. Each user role necessitates specific functionalities and views within the dashboard to effectively monitor motor performance and health. To facilitate this, wire-framing and prototyping tools such as Figma and Adobe XD were utilized to visualize user journeys and design appropriate interfaces specific to each role.

3.2. Flow of the Project

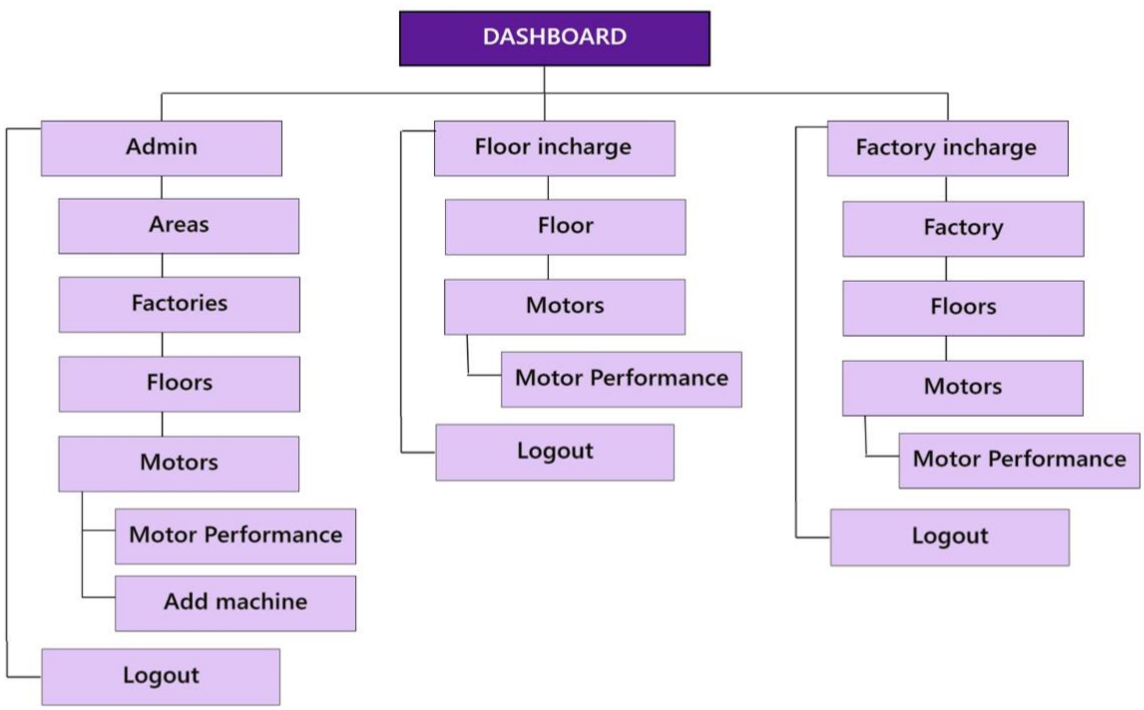

Figure 3.1 Flow of the Project

3.3. Wire-framing and Prototyping

Wire-framing serves as a preliminary step in the design process, providing a skeletal framework for the dashboard's layout and features.

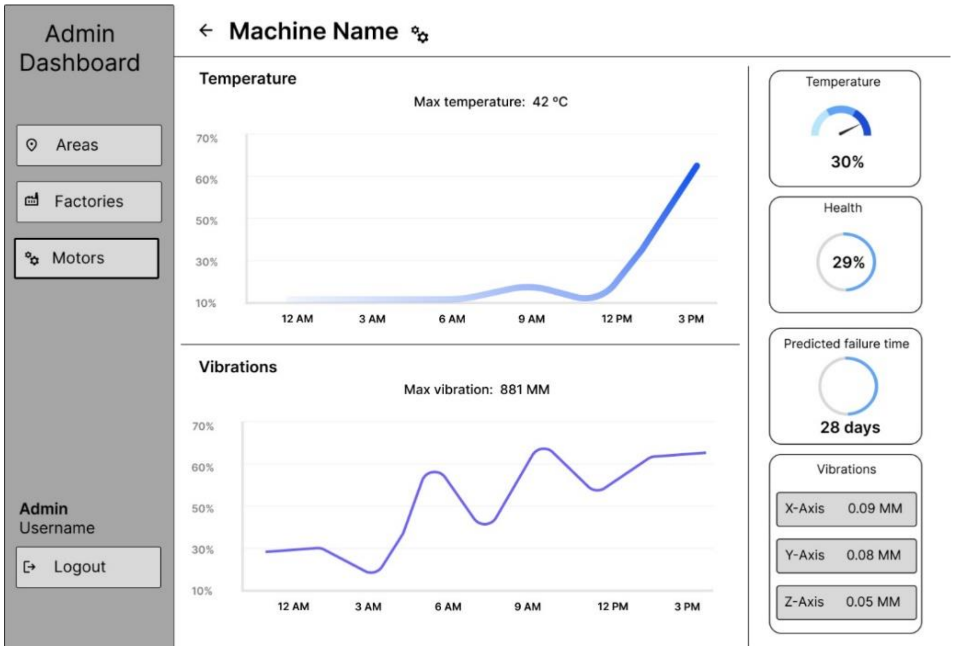

Figure 3.2 Machine Performance Wireframe

Prototypes were developed based on these wireframes to simulate the user experience and validate design decisions. Special attention was given to designing intuitive interfaces that align with the workflow of each user role.

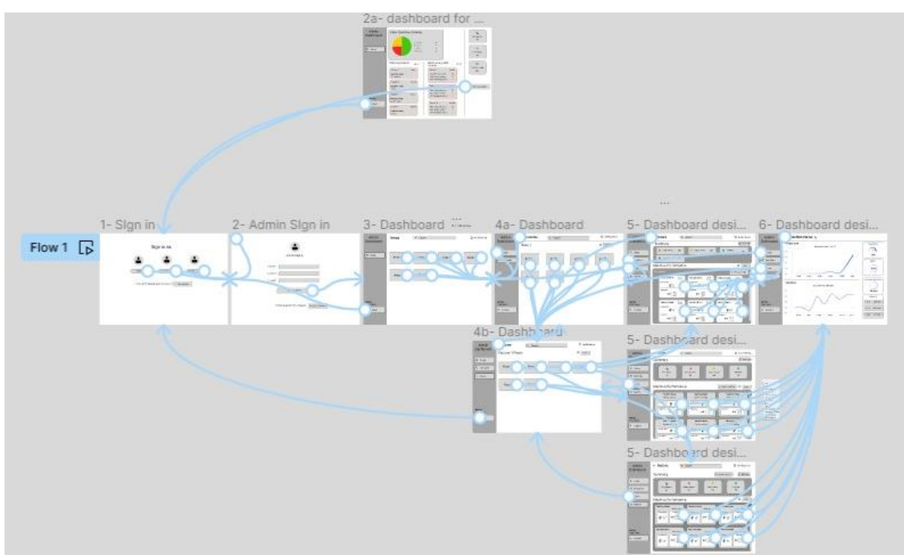

Figure 3.3 Dashboard Prototype in Figma

3.4. Dashboard Frontend Development

The frontend of the dashboard was developed using ReactJS, a JavaScript library renowned for its efficiency in handling complex real-time data. Tailwind CSS was employed to streamline the styling process and ensure a responsive and visually appealing user interface. Some other libraries, including React Data Table, Epic Charts, React Router Dom, and React Forms, were integrated to enhance the overall functionality and to ensure the industrial standards.

ReactJS was chosen for its component-based architecture, which facilitates modular development and reusability of UI elements. Moreover, its virtual DOM ensures efficient rendering of dynamic content, crucial for displaying real-time motor performance data.

3.5. Backend and API

The backend infrastructure was implemented using Flask, a lightweight Python framework suitable for developing RESTful APIs. Flask enabled rapid development of endpoints to handle data processing, authentication, and communication between the frontend and backend components.

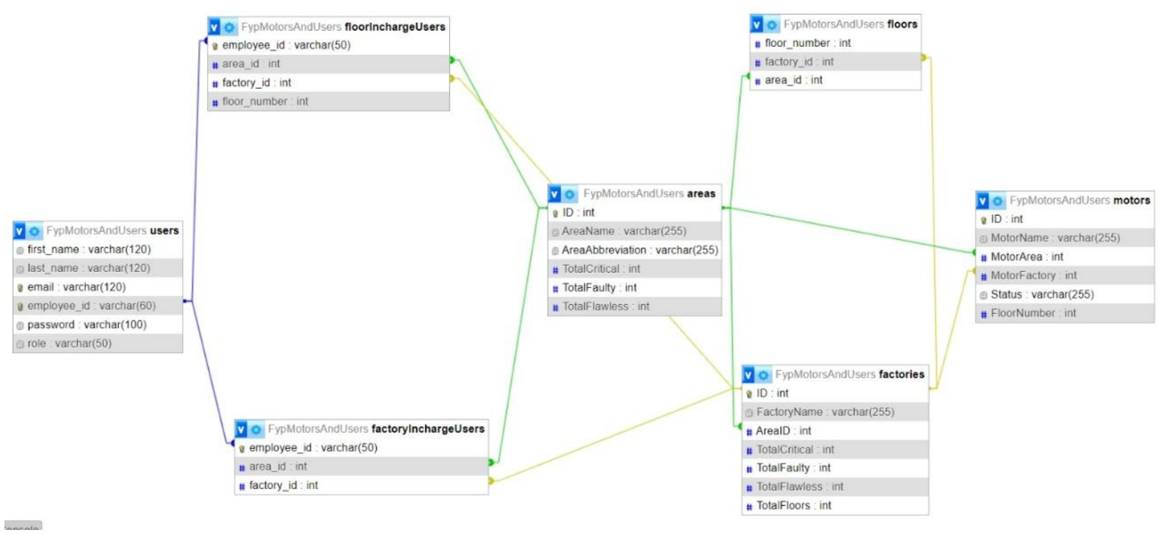

Figure 3.4 Database Schema

Data generated and processed by the system are stored and managed using MySQL, a robust relational database management system. MySQL provides a reliable and scalable solution for storing critical information related to motor performance, fault detection, and maintenance logs.

By integrating ReactJS for frontend development, Flask for backend logic, and MySQL for data management, the dashboard design ensures a user-friendly experience, seamless data flow, and efficient management of industrial motor maintenance tasks. This methodological approach ensures the successful development of a predictive maintenance solution that meets the requirements of industrial standards and effectively addresses the needs of diverse user roles within the organization.

Chapter 4 Visualization of Results

Visualizations such as graphs, charts and tables, provide intuitive insights into the performance of our predictive maintenance models and the detected anomalies. These visual representations highlight the models' ability to accurately classify motor faults and deviations from normal behavior, facilitating better decision-making and proactive maintenance interventions in industrial settings.

4.1. Dashboard Views for Different User Roles

In addition to providing visualizations of predictive maintenance results, the dashboard incorporates distinct views specifically to accommodate the specific needs and responsibilities of different user roles within the industrial setting.

Three primary user roles are considered: administrators (admin) overseeing overall system management, factory in-charges responsible for day-to-day operations and employee (user). Each role is granted access to a customized dashboard view optimized for their respective tasks and objectives.

4.2. Administrator View

The administrator view offers a comprehensive overview of system-wide performance metrics. It includes the motor health insights for all the factories.

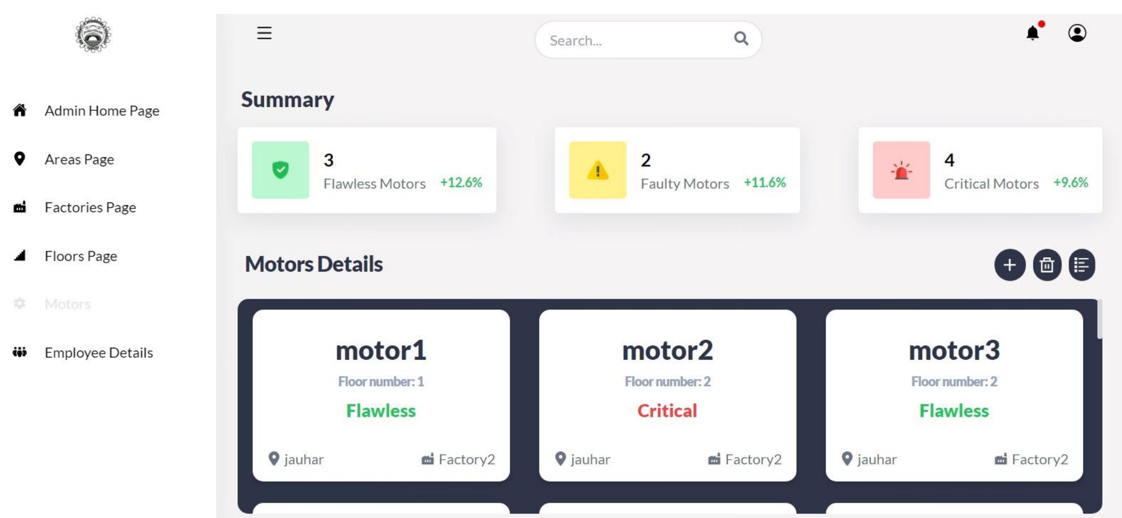

Figure 4.1 Motor Performance

Administrator can monitor the overall health of industrial motors, track the effectiveness of predictive maintenance interventions, and manage system settings and user permissions. Visualizations such as pie charts, notification system, and performance dashboards provide administrators with actionable insights to optimize system performance and resource allocation.

Administrator can view the details of factory and floor in-charges. Admin has the authority to add a new employee, update and delete the existing employees.

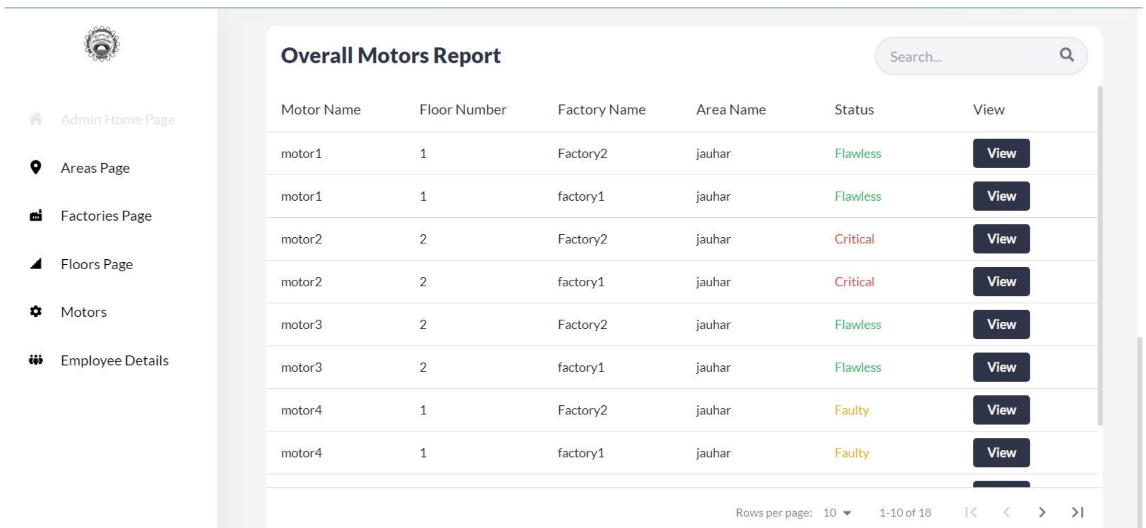

Figure 4.2 Motor Report in Admin View

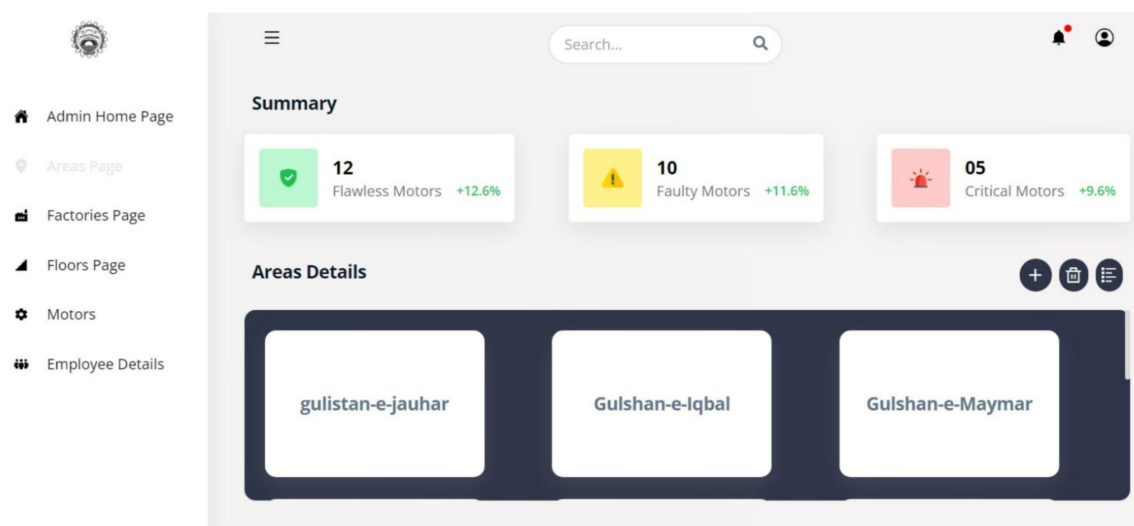

Figure 4.3 Areas Page

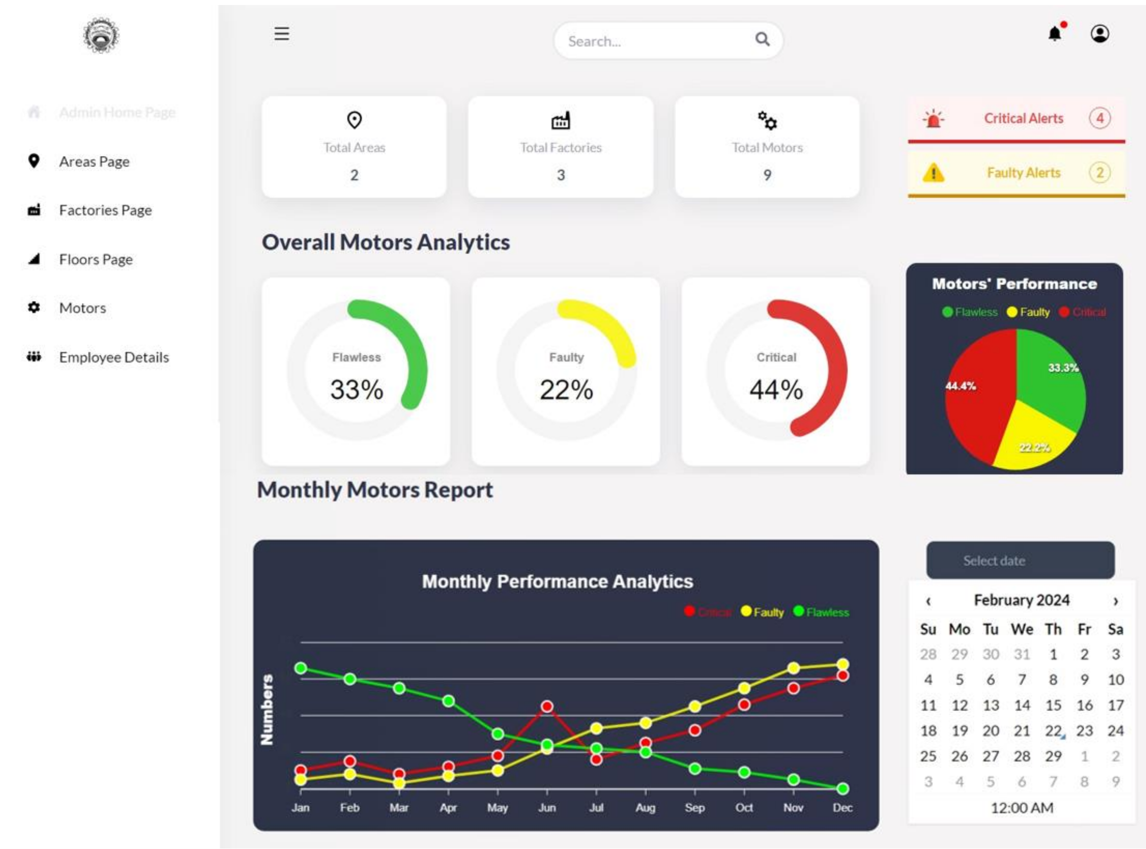

Figure 4.4 Administrator Home Page

4.3. Factory In-charge View

The factory in-charge view focuses on real-time monitoring of motor health, maintenance schedules, and anomaly alerts specific to the factory floor.

Factory in-charges can access detailed reports on individual motor performance, receive immediate notifications of detected faults or deviations, and schedule maintenance tasks accordingly. The dashboard provides intuitive visualizations particular to the operational needs of the factory, including live sensor data displays, fault heat maps, and predictive maintenance forecasts, enabling timely decision-making and proactive maintenance actions.

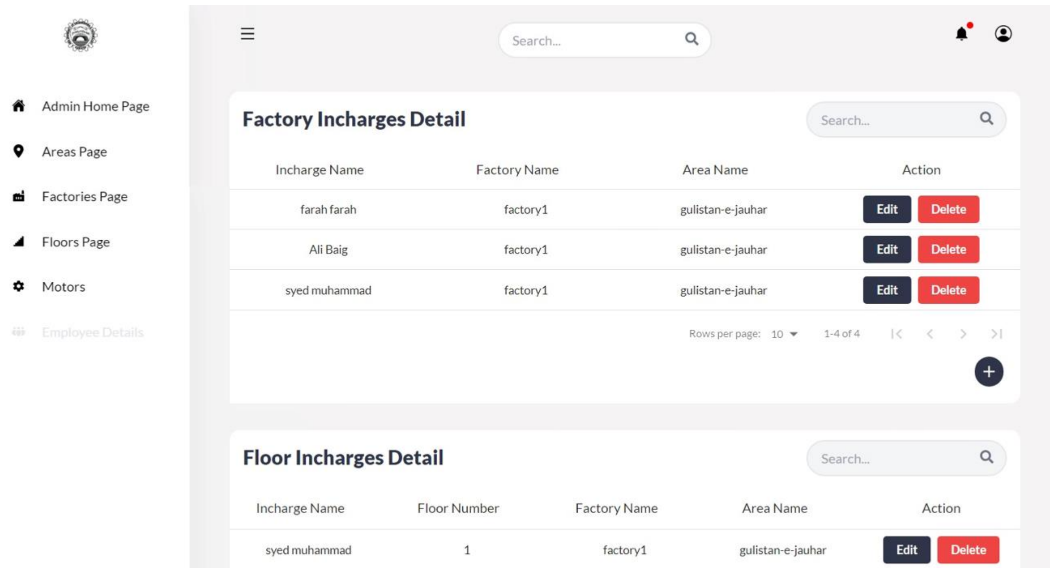

Figure 4.4 Factory In-charge Page

4.4. Floor In-charge View

The floor in-charge view focuses on real-time monitoring of motor health, maintenance schedules, and anomaly alerts specific to the floor. Floor in-charge can view the information of motors along with the name of area the factory is located and the floor number of the motor.

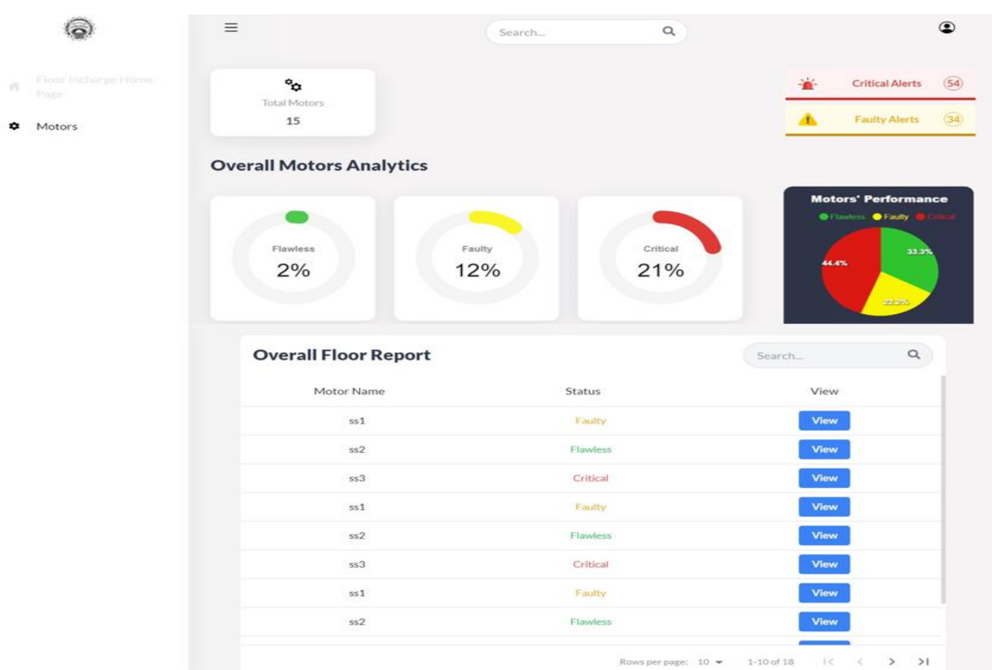

Figure 4.5 Floor In-Charge Page

Chapter 5 Conclusions

This project demonstrates the feasibility and effectiveness of employing predictive maintenance solutions for industrial motors using advanced machine learning techniques and intuitive dashboard visualization. Through a thorough literature review, we identified the significant impact of predictive maintenance on reducing downtime and optimizing maintenance costs in industrial settings. Leveraging vibration signal analysis and machine learning methodologies, including convolutional neural networks (CNNs) and bi-directional CNN-BiLSTM networks, our solution aims to accurately detect motor faults and anomalies. The development process focused on creating a user-friendly dashboard interface, with specific views to administrators, factory in-charges, and floor in-charge. Moving forward, our project will continue to enhance the scalability, adaptability, and predictive capabilities of the solution, contributing to greater productivity and sustainability in industrial operations.

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