Cloud-based Predictive Maintenance for Industrial Equipment

A major project report submitted in partial fulfillment of the requirement for the award of degree of

Bachelor of Technology

in

Computer Science & Engineering / Information Technology

Submitted by

Himanshu Pant 201330

Aryaman Singh Kanwar 201454

Under the guidance & supervision of

Mr. Arvind Kumar

Department of Computer Science & Engineering and Information Technology

Jaypee University of Information Technology, Waknaghat, Solan - 173234 (India)

CERTIFICATE

This is to certify that the work which is being presented in the project report titled "Cloud-based Predictive Maintenance for Industrial Equipment" in partial fulfillment of the requirements for the award of the degree of B.Tech in Computer Science And Engineering and submitted to the Department of Computer Science And Engineering, Jaypee University of Information Technology, Waknaghat is an authentic record of work carried out by Himanshu Pant(201330) & Aryaman Singh Kanwar(201454) during the period from August 2023 to May 2024 under the supervision of Mr. Arvind Kumar, Department of Computer Science and Engineering, Jaypee University of Information Technology, Waknaghat.

Student Name: Himanshu Pant	Student Name: Aryaman Singh Kanwar
Roll No.: 201330	Roll No.: 201454

The above statement made is correct to the best of my knowledge.

Mr. Arvind Kumar

Assistant Professor (Grade-II), CSE/IT

Computer Science & Engineering and Information Technology Jaypee University of Information Technology, Waknaghat

Declaration

I hereby declare that the work presented in this report entitled **'Cloud-based Predictive Maintenance for Industrial Equipment '** in partial fulfillment of the requirements for the award of the degree of **Bachelor of Technology** in **Computer Science & Engineering / Information Technology** submitted in the Department of Computer Science & Engineering and Information Technology**,** Jaypee University of Information Technology, Waknaghat is an authentic record of my own work carried out over a period from August 2023 to May 2024 under the supervision of **Mr. Arvind Kumar** (Assistant Professor (Grade-II), Department of Computer Science & Engineering and Information Technology).

The matter embodied in the report has not been submitted for the award of any other degree or diploma.

(Student Signature with Date)
Student Name: Himanshu Pant
Roll No.: 201330

(Student Signature with Date)
Student Name: Aryaman Singh Kanwar
Roll No.:201454

This is to certify that the above statement made by the candidate is true to the best of my knowledge.

(Supervisor Signature with Date)
Supervisor Name: Arvind Kumar
Designation: Assistant Professor (Grade-II)
Department: Computer Science & Engineering and Information Technology
Dated:

Acknowledgement

We would like to express our sincere appreciation to our dedicated **Mr. Arvind Kumar** for their invaluable guidance and support throughout the development of our project, titled "**Cloud-based Predictive Maintenance for Industrial Equipment.**"

So far, we have made significant progress due to the skills and dedication of our supervisor. Their contributions so far have been a great help for us in running the early phase of our project successfully. We also believe that they will continue with their guidance as we go beyond the initial phases of the project.We thank our supervisor for being so generous as he evaluates our work in readiness for the final meeting. We are sure that their ideas and advice will greatly assist us in tuning up the project to make it perfect.Thank you very much, for supervisory mentorship and guidance. We believe that with the involvement of these individuals, we can complete the project successfully on time.

TABLE OF CONTENT

List of Figures

List of Abbreviations, Symbols or Nomenclatures

Abbreviations	Meaning	Page No.
CPM	Critical Path Method	2
PdM	Product Data Management	11
SMEs	Small and Medium-sized Enterprise	12
LSTM	Long Short-Term Memory	14
ML	Machine Learning	17
IOT	Internet of Things	18
EHM	Engine Health Management	19
IIOT	Industrial internet of things	23
SQL	Structured Query Language	29
SVM	Support Vector Machine	56

Abstract

The main objective is to develop and deploy an industry specific cloud based predictive maintenance systems (CPM). Predictive maintenance is crucial in modern industrial environment because it increases equipment dependability, reduces losses due to interruptions and maximizes production efficiency in whole. The modern CPM System using latest data analytics, ML algorithm and cloud computing technology will help to innovate in monitoring and controlling the important equipment.

The system starts with a strong data collection and aggregation process that acquires live sensor data from industrial equipment, parameters like temperature, vibrations, operational variables etc. Such transmits this data directly to the centralized cloud repository whose basis lies in further analysis. These data are then used by machine learning algorithms from the simple regressions models up to the neural networks which detect such patterns predicting upcoming equipment failures. This study seeks to create forecasting predictive models using both historic and current information focusing on use and wear patterns, environmental factors, and previous maintenance records so as to generate precise estimates.

The scalable and flexible nature for data processing provided by utilizing cloud computing infrastructure is critical in making the system efficient. It allows efficient storage, retrieval, and analysis of huge data sets that help in developing precise predictive models. The interface is user-friendly with the ability to view equipment conditions, predictable failures, and historical trends. Additionally, it automatically gives out prompt warnings and messages that allow the team to anticipate any problems as well as organising for maintenance services before they get worse. The project is based on combining cloud technologies with machine learning and real time data. This will enable proactive industrial maintenance and bring us into the age which is compatible with the principles of Industry 4.0 thereby creating more operational efficiency and economy of production.

CHAPTER 1: INTRODUCTION

1.1 Introduction

The drive for operational excellence is associated with advanced technology in the changing environment of industrial operation. Recognizing the imperative for a revolutionary approach to maintenance practices, this major project introduces a groundbreaking initiative: Using cloud-based predictive maintenance on industrial equipment.

Equipment downtime affects operational efficiency, productivity, and ultimately, bottom-line profitability of industrial sectors constantly. Traditional maintenance strategies that are reactionary and schedule-based appear inadequate for meeting the challenges of contemporary intricate and interactive industrial environment. This new era called industry 4.0 emphasizes the use of advanced technologies to redefine how we do things with industries. Therefore, in terms of the transformation of this process, our project is essential. In it, we are going to solve the most important aspect of the transformation – i.e. the predictive maintenance – through the novel combination of cloud computing, data analytics, and machine learning.

This major project aims at developing a customised CPM that will exist in the cloud and be targeted to industrial equipment use. The philosophy behind the core revolves around harnessing the strengths that cloud infrastructure offers to exceed the limits of the typical maintenance models. Therefore, an imagined system supports online diagnosis, assessment of condition, and forecasting on the imminent breakdowns of heavy-duty machinery. The CPM system incorporates state-of-the-art machine learning algorithms designed to shift the maintenance paradigm from reactive to predictive, with the aim of anticipating and mitigating potential problems before they affect operations.

The core reason why this project is important is to solve the intrinsic inefficiencies and restrictions that come with conventional maintenance approach. However, reactive maintenance of fixing equipment only when it fails has its downside by producing unplanned downtime, increasing maintenance costs, and impairing productivity. Whereas planned preventive maintenance might occasion some uncalled-for interventions and wastage of resources while the equipment is still in perfect operating condition. To this end the CPM system tries to identify the problems as quickly as possible in critical machines so that necessary measures can be taken promptly.

The cloud-based architecture lies at the heart of the project's effectiveness, which has scalability, flexibility, and efficiency when dealing with large volumes of real-time and historical data. The system utilizes cloud computing infrastructure to allow for the proper storage, retrieval, and analysis of different sets of data collected from various industrial equipment sensors. Such integration improves the predictability as well as makes the models easily scalable and economically viable especially in industries.

Our project is in line with the fundamental concept of Industry 4.0, which uses technology to improve processes and efficiency. This paper will discuss the technical details, approaches, and expected results of the Cloud-based predictive system in the forthcoming sections. We try to show how this project can change approaches to equipment operation for industrial use: it will be proactive to eliminate downtime and promote reliability, which ensures the competitiveness and durability of industrial organizations in future.

1.2 Problem Statement

The ongoing challenge of an equipment downtime in the modern industrial landscape is a major barrier to the pursuit of highest levels of efficiency and competitiveness. Many of today's complex and interrelated industrial systems require more than traditional maintenance strategies based on scheduled interventions or reactive response to failures. Underserved downtime poses a serious threat to the sustainability of commercial activities and is usually a cause of considerable financial losses together with low production.

This emphasizes the disadvantages of reactive maintenance that requires repair only after a failure has occurred leading to high costs of emergency repairs which affect production schedules. The preemptive scheduled preventive maintenance is often uncalled for because it is meant to prevent issues which may never occur. An innovative option needs to be proposed here which will eradicate the defects of traditional maintenance and introduce a preventive approach.

In addition, the emergence of a new industrial revolution (Industry 4.0), which combines smart technologies and data-informed management, requires to reconsider the approach to technical support issues. For instance, the inability to provide live monitoring and forecast on industrial machines' health makes it hard to harness the benefits of such technologies in this context. A new way through modern technologies of prediction and prevention of any failure in devices is urgent nowadays. It will lower costs of stopped devices and save money and time.

This major project is aimed at addressing the above-mentioned pressing challenges by putting forward a Cloud-based Predictive Maintenance (CPM) system purposely for industrial equipment's .The project acknowledges the need to move from schedule and reactive maintenances to a proactive one that utilizes cloud computation, data analytics, and machine learning. This strategy is aimed at providing end-to-end solution covering financial, operational, and Industry 4.0 transformation impacts of equipment downtime and sustaining industrial operation in the era of digitalization.

1.3 Objectives

These are the objective of developing our project: -

- **Improved Equipment Lifespan:**

  The CPM system aims at modernizing industrial equipment lifespan in the dynamic environment of industry operations.Predictive maintenance techniques are employed in order to minimize the wear and tear on key components, resulting in increased utility of these items in operation.

  Advanced data analytics combined with machine learning algorithms forms the core of this project.The CPM system uses historical and real-time data for predicting and preventing equipment failures even before they happen.This helps in preventing unexpected shutdowns and greatly increases longevity for essential facilities.

- **Remote Accessibility:**

  In addition to predictive maintenance, the CPM system presents a new aspect of remote accessibility for equipment health and maintenance information.This feature allows the teams to monitor and act on issues from wherever they may be located in a connected world where high operational flexibility prevails.In an easy-to-use and secure environment, maintenance teams can monitor the equipment condition, initiate repair works and optimize the equipment performance even without physical presence at the site of action.Moreover, it increases the effectiveness of maintenance operations and provides a way for making quick and cost effective decisions.

- **Continuous Improvement and Reduced Downtime:**

  In addition, the CPM system is not just a tool, but a way of inducing a culture of continuous improvement into workplaces in industry.The system functions as a dynamic repository for continuous performance analysis and optimization through the provision of real-time data and insights.The continual process of learning from operational behavior helps in data-guided decision-making as the organizations improve their maintenance practice and operation processes.

This results in a significant decrease in downtime, increased production overall, and better operation efficiency.This enables teams to react quickly to new emergencies, to introduce specific changes following factual observations and, to repeatedly improve equipment reliability and performance.

Put simply, the triad of predictive maintenance, remote accessibility, and continuous improvement of industrial operations through the Cloud-based Predictive Maintenance system works towards two main goals of extending the useful life of the equipment and preparing operations for sustainable future performance in an era of rapid technological advances and

1.4 Significance and Motivation of the Project Work

1. Optimizing Operational Efficiency:

This project is an important step towards enhancing effective management in industries for efficient operations.The system enables organizations to shift away from reacting to equipment malfunction towards prevention.This enhances minimal downtime and at large improves efficiency in the industrial ecosystem.

2. Cost Reduction and Resource Optimization:

This can lead to unplanned downtime and emergency maintenance activities with huge monetary loses.A good CPM system is expected to largely minimize these costs through anticipation of and prevention from equipment breakdowns.Predictive maintenance is usually a proactive approach thus ensuring prudent use of maintenance resources as well as mitigating any cases of unplanned repairs.

3. Prolonging Equipment Lifespan:

Organizations which attempt to get optimum returns on invested assets concentrate on extending the useful life of industrial equipment.The project systematically reduces wear and tear through predictive maintenance strategies, thereby prolongs usage of critically important assets, avoiding early replacements that result in higher cost.

4. Aligning with Industry 4.0 Principles:

As highlighted in the four principles of industry 4.0, this project focuses on incorporating various advanced technologies into the industrial development process for better efficiency.Thus, CPM system leverages the latest technologies such as cloud computing, data analytics and machine learning which are well supported by the current trends of digitization.

5. Remote Accessibility and Operational Flexibility:

Improved access to remote health and maintenance data is becoming a critical aspect of achieving operational flexibility.In a time of remote working and instantaneous decision making, this function equips the maintenance team with means of monitoring, analyzing, and responding to equipment problems from every part of the globe, making operations swift.

6. Fostering a Culture of Continuous Improvement:

Cultivating a culture of continuous improvement within an organization is facilitated by the CPM system.The system provides up to date data and insights that drive informed decision making and help to continuously improve maintenance practice.Such continuous improvement results in less downtime thus more productivity and optimal processes operation.

7. Sustainable and Competitive Operations:

For effective sustainable industrial operations, there is a need for a strategic approach to maintenance.Predictive maintenance is one of the core values that make this project eco-friendly. It is also an element, which allows companies to stay ahead during these times of changing industrial landscape.

Finally, the essence and stimulation for the project are its ability to recreate maintenance approaches, maximize performance, and conform to Industry 4.0 concepts.The Cloud-based Predictive Maintenance system is therefore an example of affordable, green, and high tech industrial operation addressing its current concerns.

1.5 Organization of Project Report

To successfully communicate the significance, methods, and results of the ground-breaking endeavor centered on cloud-based predictive maintenance for industrial equipment, the project report's organization is crucial. To ensure that the goals, procedures, outcomes, and implications of the project are presented with clarity and coherence, a careful framework is necessary to lead the reader through its intricacies.

The project report opens with an engaging introduction that provides context for the whole undertaking. The urgent problem of equipment failure in contemporary industrial processes is illustrated in this introduction in a clear and concise manner, highlighting the negative effects it has on productivity, operational effectiveness, and total profitability. In order to smoothly transition into the project's major idea—the integration of cloud-based predictive maintenance using cutting-edge technologies like data analytics and machine learning—it is necessary to emphasize the need for a new approach to maintenance operations.

The project report opens with an engaging introduction that provides context for the whole undertaking. The urgent problem of equipment failure in contemporary industrial processes is illustrated in this introduction in a clear and concise manner, highlighting the negative effects it has on productivity, operational effectiveness, and total profitability. In order to smoothly transition into the project's major idea—the integration of cloud-based predictive maintenance using cutting-edge technologies like data analytics and machine learning—it is necessary to emphasize the need for a new approach to maintenance operations.

The project report's following sections are carefully laid out to give readers a thorough grasp of the approach used to implement cloud-based predictive maintenance. This comprises an in-depth investigation of the combination of machine learning, data analytics, and cloud computing—the trifecta that serves as the foundation for the suggested remedy. Every element is broken down, explaining its function and how it fits into the larger scheme. The justification for selecting these technologies is sound, emphasizing their ability to bring in a new era of industry 4.0-compliant maintenance procedures.

Going forward, the project report outlines the particular advantages of implementing cloud-based predictive maintenance while methodically detailing the implementation process and addressing any potential obstacles. Experiments, case studies, and real-world examples are used to support the effectiveness of the suggested strategy. This empirical data highlights the project's potential to change industrial maintenance paradigms and supports the project's transformative impact.

The project report's conclusion restates the importance of the cloud-based predictive maintenance initiative by briefly summarizing the main conclusions. It restates the advantages that industrial sectors stand to gain from increased operational effectiveness, decreased downtime, and increased profitability. Furthermore, the conclusion opens up new directions for predictive maintenance research and development, promoting continuous innovation in this ever-evolving field.

The project report is structured essentially like a well-chosen journey, taking the reader from the problem statement to the suggested solution and ending with a strong argument for the revolutionary potential of cloud-based predictive maintenance in industrial operations. The narrative in each section flows naturally from the one before it, convincing the reader of the project's value and significance for the changing field of industrial maintenance techniques.

CHAPTER 2:
Literature Survey

2.1 Overview of Literature Survey

<u>Tackling Industrial Downtimes with Artificial Intelligence in Data-Driven Maintenance (2023)</u>

There is increased use of artificial intelligence in maintenance driven by data to address industrial breakdowns.These predictive maintenance models are supported by Artificial Intelligence, which is used to analyze different parameters to produce predictive forecasts based on user patterns so that maintenance teams can be warned about possible equipment breakages.The critical issues arising here include data management and analysis, interpretation of machine learning models, cost and investment, data accessibility and quality, adoption and change management, and privacy and safety aspects.The criticality of overcoming these challenges cannot be neglected if the SMEs in any specific industry are to enjoy the benefits of predictive maintenance approaches.Using AI for predictive maintenance helps avoid downtime, reduces cost, and enhances productivity in general.

<u>From Corrective to Predictive Maintenance — A Review of Maintenance Approaches for the Power Industry (2023)</u>

This paper titled “from corrective to predictive maintenance—a review of maintenance approaches for the power industry” comprehensively reviews maintenance approaches for the power industry such as corrective, predictive, and predicative.Predictive maintenance reduces downtime, increases equipment reliability, and prolongs equipment life.This review depicts how these maintenance methods have been used for the purpose of informing maintenance planning, equipment monitoring, and supervisory systems development and design.This paper provides older traditional approaches commonly used in maintenance activities and the latest computer analytics methods of task performance and inference for failure detection.This is essentially an attempt to summarize the modern approach towards engineering practice that is guided by Artificial Intelligence concept and industrial revolution.This article gives a glimpse of what is being witnessed out there, the issues surrounding it and how far they have spread across different industries such as the power sector.

On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges (2022)

PdM refers to a kind of predictive maintenance strategy employed to increase production capacity and raise factory output in advance of the equipment breakdown.It is an integral part of Industry 4.0 where Machine maintenance gets digitally done .

Models for predictive maintenance uses a number of tools, including cyber-physical systems, the industrial Internet of Things, big data, digital twin, augmented reality, artificial intelligence, machine learning, and deep learning.

One of these main challenges is to predict when it should be necessary to maintain assets at a particular certain second time.

There are a number of stages involved in predictive maintenance; namely, data collection, data cleaning, model development, model evaluation, and model implementation.

There are a number of problems, when predictive maintenance is introduced: some financial limits, some organizational limits, limits with data sources, some limits with machine repair activity as well as some limits with deploying industrial predictive maintenance models.

Exploration of Production Data for Predictive Maintenance of Industrial Equipment: A Case Study (2023)

The case study explores the potential of using only manufacturing states in predictive maintenance of industrial equipment.

This study focuses on predictive maintenance that is mainly derived from several sensors or industrial data gathered for a number of months.

There are several companies in the Netherlands where the multi-case study has been undertaken to find the reasons why only some of them managed to implement predictive maintenance.

Data obtained from sensors and industrial systems are of little value unless they are presented in form of meaningful context which can only be understood by the relevant persons.

Asset owners and maintainers must use PdM to schedule timely and intelligent decision making about maintenance on the basis of the real or projected condition of those physical assets.

The study discusses the components of decision-making and maintenance strategy that are necessary for predictive maintenance.

To conclude, the case study indicates the value of the usage of production data for predictive maintenance of the industrial machinery.Companies can enhance their maintenance through the analysis and processing of data from sensors and industrial systems that has been recorded, which will improve the performance and reduce downtime of their equipment.

A Systematic Mapping Study of Predictive Maintenance in SMEs (2022)

A systematic mapping study of predictive maintenance in SMEs was done with a view of providing information to researchers.The study looked at socio-demographic information surrounding predictive M in SMEs, as well as its distinctive features, major challenges, and best practice.The study reviewed published works during this period (2010–2020) on PdM in SMEs to show main anticipated Pm challenges and requirements of SMEs.The study and some of the relevant papers have pointed out some problems in data management, machine learning model interpretability, cost and investment, data availability and quality, adoption and change management as well as privacy and security.These gaps should be addressed and it is necessary for predictive maintenance programs to be successfully implemented in the small and medium sized enterprises (SMES).

Predictive Maintenance of Machine Tool Systems Using Artificial Intelligence Techniques Applied to Machine Condition Data(2022)

Applying artificial intelligence techniques to two critical elements of the machine tool system for predictive maintenance is the subject matter of the article titled "Predictive Maintenance of Machine Tool Systems Using Artificial Intelligence Techniques Applied to Machine Condition Data".The work points out the necessity of the data-based maintenance and using the artificial intelligent forecasting approach for machine tool system failures.The study explores the challenges involved in data management and analysis, interpretability of machine learning models, cost and investment, data availability and quality, adoption and change management as well as privacy and security issues.Therefore, this study highlights the importance of addressing these challenges when planning predictive maintenance initiatives for industries.Other related articles in the search results offer more understanding on the state-of-the-art algorithms used for data-driven maintenance, the challenges and prospects associated with the use of digital information at a convergence point of big data analytics and supply chain management as well as use of machine learning approach for condition

Predictive Maintenance and Intelligent Sensors in Smart Factory: Review (2021)

The article "Predictive Maintenance and Intelligent Sensors in Smart Factory: The review "Predictive Maintenance" analyses recent academic discourse on predictive maintenance and intelligent sensors in smart factories.To this end, the study is contemporary to serve as a guide for future research challenges and classification.Systematic review of literature utilizes burst analysis, co-occurrence analysis of keywords, and cluster analysis.This shows the rising numbers of articles on the key research terms, suggesting the growing significance of predictive maintenance with regard to Industry 4.0 technologies.To give an overview on the SIPM, the study suggests employing full-text analysis of the relevant scientific literatures.This study will provide an overview and summary of the trend of intelligent sensors for predictive maintenance in smart factory considering industry 4.0 technology and the increasing significance of predictive maintenance in modern factories.

LSTM for predictive maintenance of industrial equipment based on machine learning(2022)

The search results provide several articles related to the use of Long Short-Term Memory (LSTM) models for predictive maintenance of industrial equipment based on machine learning. One article proposes a general Predictive Maintenance (PdM) framework based on Internet-of-Things technology, cloud computing, and total productive maintenance[1]. Another article discusses the increasing importance of predictive maintenance for businesses that rely on industrial machinery to operate and highlights the use of LSTM models for predictive maintenance . A third article presents an LSTM-based model for predictive maintenance that can detect the incipient breakdown of a system and avoid environmental consequences of equipment failure . A fourth article proposes a predictive maintenance model using RNN and LSTM models to identify and forecast heavy machine failures . Finally, a fifth article proposes a machine learning-based predictive maintenance approach to predict the remaining useful life of production lines in manufacturing . These articles demonstrate the growing interest in using LSTM models for predictive maintenance of industrial equipment and highlight the potential benefits of this approach.

Cloud Computing for Industrial Predictive Maintenance Based on Prognostics and Health Management (2020)

They show various documents with information related to prognosis and health management in industrial predictive maintenance using cloud computing. Here are some key points from the search results:

1. Prognosis Approach Based on Cloud Computing : Prognosis as a service using cloud computing and the concept of multitenancy .

2. Benefits of Cloud-based Predictive Maintenance : A large benefit of cloud-based predictive maintenance management include positive economic impacts with cost reduction.

3. Cloud-based Predictive Maintenance for Intelligent Manufacturing : Mobile Agent-enabled approach for timely information in a cloud-based paradigm of predictive maintenance.

4. Google Cloud Platform for Predictive Maintenance : The Google Cloud Platform's products and solutions for industrial predictive maintenance include Cloud IoT Core, Cloud IoT Edge, BigQuery,cloud data flow and cloud ML Engine.

5. Accelerating the Industrial Revolution with Predictive Maintenance : The Industrial revolution of today is underpinned through several technology trends that include big data, cloud computing, machine learning, edge computing as well as the internet of things which providethe predictive Maintenance .

The utilization of the cloud services highlights an increase in the importance of cloud computing industrial predictive maintenance with a reduction of cost, provision of real time information, and enablement of new business models. Combining cloud-based solution with advanced technology is reshaping how predictive maintenance is applied in an industrial situation.

<u>A new paradigm of cloud-based predictive maintenance for intelligent manufacturing (2015)</u>

The articles shed light on cloud-based predictive maintenance and intelligent manufacturing. The first two papers are providing a cloud–mobile agent–based (CMA) prediction for immediate information and manufacturing challenges. The third article from Google Cloud Blog highlights on the strategy to be used when undertaking industrial predictive maintenance by discussing how big data, cloud computing, machine learning, edge computing, and Internet of things can be utilized to enhance the operational efficiency of manufacturing factories . Articles number four analyze predictive maintenance in decision making for smart manufacture. Article five on full predictive maintenance reference solution is comprised of the following Google Cloud Platform products: Cloud IoT Core, Cloud IoT Edge, big data and data processing tools like BigQuery and Cloud Dataflow, and machine learning platforms such as Cloud ML Engine. The predictive maintenance reference solution The resources give a detailed description of the approaches, technologies and solutions that can be used for cloud-based predictive maintenance in smart manufacturing.

Cloud-Based Predictive Maintenance and Machine Monitoring for Intelligent Manufacturing for Automobile Industry (2019)

Predictive maintenance and machine monitoring in cloud-based intelligent manufacturing of automobile is an emerging field of research. Cloud computing and mobile agent technology in predictive maintenance for intelligent manufacturing. Here are some key points from the search results:

1. Cloud-Based Predictive Maintenance: Propose a new paradigm of cloud-based predictive maintenance to acquire information timely, sharing, using it in order to improve fault diagnosis, remaining service life prediction, and maintenance scheduling accuracy.

2. Predictive Maintenance in Automobile Industry : Direct monitoring of mechanical condition of plant equipment in order to establish actual mean time to failure is fundamental for the automobile to reduce downtime and efficiency.

3. Mobile Agent Technology : The new cloud-based paradigm for predictive maintenance utilizes a low-cost cloud sensing and computing sensor node with the embedded Linux OS, mobile agent middleware, and open source numerical libraries. Mobile agent distributes analysis algorithm into sensing and computing node for local processing of data and interaction to other agent

4.Benefits of Cloud-Based Predictive Maintenance : One of the advantages of cloud-based predictive maintenance is increased system flexibly and adaptability, less raw data transmitted, and instantaneous response to dynamic changes of operations or tasks.

Firstly, these resources cover the different approaches, technologies as well as the solutions that can be implemented to the cloud based predictive maintenance in intelligent manufacture, especially in automaking.

Cloud-enhanced predictive maintenance (2016)

The concept of cloud based predictive maintenance is explained through its search results. Here are the key points from the search results:

1. Cloud-Enhanced Predictive Maintenance Framework**: This study aims at putting forth a framework and approach to manage, process and archive data concerning maintenance, production and factory data emanating from the first lifecycle phase up to the operation and maintenance phase. Wide-information-content based cloud-based approach to enhance the condition-based predictive maintenance decision-making.

2.Predictive Maintenance and Cloud Computing**: Predictive maintenance is a technique which involves using condition monitoring's data to anticipate the status of the machines and then making decision on the basis of it. Therefore, cloud computing is used for data capturing and analysis in real-time, in order to forecast and avoid the disuse of establishments, thereby reducing maintenance costs and improving production efficiency .

3.Benefits of Cloud-Based Predictive Maintenance**: Predictive maintenance using the cloud provides flexibility, less raw data transmission and instant responsiveness with respect to dynamic operational changes and evolving tasks.

4. AI and ML in Predictive Maintenance**: Predictive maintenance, which is driven by AI and ML, involves the use of data analytics, sensors, and ML algorithms to foresee equipment failure. This entails scheduling of repairs and maintenance with an aim of reducing downtime for lower maintenance cost.

They point out the increasing role of cloud computing and Artificial Intelligence (AI), Machine Learning (ML) and other new technologies in predictive maintenance and its economic feasibility, improved efficiency and prognostic maintenance.

Cloud-Based Asset Monitoring and Predictive Maintenance in an Industrial IoT System(2020)

Cloud-based asset monitoring and predictive maintenance in an industrial IoT system is a burgeoning area of study and development. The search results include a variety of materials connected to this issue, such as academic papers, industry blogs, and research reports. Here are a few highlights from the search results:

1.Cloud-Based Asset Monitoring and Predictive Maintenance: Using cloud-based asset monitoring and predictive maintenance in an industrial IoT system includes regular monitoring of numerous factors, such as temperature and vibrations, to spot abnormalities and predict probable equipment breakdowns.

2. IoT Asset Tracking and Preventive Maintenance: IoT asset monitoring and predictive maintenance solutions work together to supply real-time insights and notifications when equipment and other assets are in motion, are not working properly, or are showing evidence of deterioration.

3. Cloud-Based Predictive Maintenance Advantages: Cloud-based predictive maintenance provides advantages such as increased system flexibility and adaptability, less raw data transmission, and fast response to dynamic changes in operations and activities.

4.Cloud-Based Predictive Maintenance Applications: Cloud-based predictive maintenance can be used in a variety of industries, including manufacturing, mining, wind and solar farms, and construction activities, to avoid equipment problems from occurring and causing business downtime.

These resources emphasise the growing relevance of cloud-based asset monitoring and predictive maintenance in industrial IoT systems, which provide advantages such as cost savings, increased efficiency, and proactive maintenance techniques.

A Cloud-based Approach for Maintenance of Machine Tools and Equipment Based on Shop-floor Monitoring (2015)

Several materials about cloud-based monitoring of shop floor machines, equipment, etc. Here are some key points from the research .

1. The paper entitled “A cloud-based method for condition-based preventive maintenance through shop-floor monitoring” highlights a maintenance methodology involving the integration of condition-based maintenance in the shop-floor monitoring system. The framework utilizes shop-floor machine tool data for condition-based preventive maintenance operations via information fusion. This approach is evolved to a software service on a Cloud environment.

2. EHM is an online platform for equipment health and maintenance. It enables users to analyze equipment health and provide preventive maintenance. The application of EHM is beneficial in decreasing equipment uptime, increasing reliability, and maximizing operation and maintenance costs.

3. The cloud-based manufacturing process monitoring framework has been developed with focus on tool condition monitoring and remaining useful life prediction for online smart diagnosis services. This framework applies cloud computing in delivering web based smart diagnosis procedures for maintenance and decision support .

Cloud based solutions are increasingly significant in the issue of machine tools equipment maintenance, leading to cost saving, improved efficiency, and anticipation methods.

Machine Learning approach for Predictive Maintenance in Industry 4.0 (2018)

There are many sources regarding machine learning for predictive maintenance into industry 4.0 available in the search results. Machine Learning Architectures for Predictive Maintenance. Specifically, random forest. As proof of the possibility to apply machine learning for predictive maintenance in industrial facilities these were shown on real industry examples.

These resources also describe the current position and issues associated with predictive maintenance in an Industry 4.0 setting. Predictive maintenance is very important in industry 4.0 discourse, but some issues remain underinvestigated and unresolved .

Generally, the search results show that the machine learning methods like Random Forest are becoming more attractive for predictive maintenance related to IoD. The resources offer important observations on the present positioning, difficulties, as well as prospects of machine learning for predictive maintenance within industry 4.0.

<u>A data-driven predictive maintenance framework for injection molding process(2022)</u>

“A Data Driven Predictive Maintenance Framework 9 injection Molding Process”, proposes a framework on how the predictive maintenance model of the injection molding can be developed on integration of different data sources and usage of both cloud and edge computing. This approach aims at lowering maintenance expenses, improving product quality andenhancing production efficiency in the plastics industry.9 An example involves a case study monitoring the cooling system during the injection molding with the purpose of showing its use.

This framework employs Industry 4.0 technology which include cyber-physical system, IoT, edge and cloud computing, new sensor and vision-based system as means for impro`ving production and enterprise system. The design supports data driven predictive maintenance system that helps cut down the maintenance expense and enhance product quality and production output.

The South Carolina Research Authority (SCRA) has provided financial support for the proposed framework through the SCRA-Academic Collaboration Team Feasibility Grants and the Clemson Forward R-Initiatives Programme: Clemson Research Fellows.

Predictive maintenance scheduling for multiple power equipment based on data-driven fault prediction (2022)

This is a case search that includes various materials about predictive maintenance scheduling, multiple powerequipment data-driven fault prediction. Predictive maintenance reduces downtime, enhances equipment reliability, and raises asset life. The proposed framework employs data driven fault prediction to design optimal preventive maintenance schemes which seek to minimize maintenance costs and increase overall operational efficiency in the process. Predictive maintenance is a forward strategy that employs data-based information and technological systems to forecast when equipment is about to develop problematic issues or fail completely and therefore schedule appropriate actions prior to a specific asset failure. Therefore, there is need to apply condition based maintenance using predictive analytics to efficiently allocate resources to prevent breakdowns as well as extend the asset lifetime. Predictive maintenance, customized maintenance schedules, optimization of asset management and performance, and reduction of operational disruptions are some of the benefits highlighted by the resources..

A heuristic approach on predictive maintenance techniques: Limitations and scope (2022)

It lists various sources concerning a heuristic approach towards PMT, the limitations and their scope. The brief resource describes industry 4.0 predictive maintenance techniques available for various applications. The resources stress how predictive maintenance reduces downtime, improves equipment reliability, and extends the life of assets. This also covers the limitations and scope of predictive maintenance techniques, such as data management and analysis, interpretability of machine learning models, cost and investment, data availability and quality, adoption and change management, and privacy and security issues. These resources highlight that it will be important to combine efforts and to make the appropriate implementation of such PMs in industrial areas. These resources provide useful information about the current situation, problems, and possibilities of using predictive maintenance in Industry 4.0.

Toward cognitive predictive maintenance: A survey of graph-based approaches (2022)

The paper "Toward Cognitive Predictive Maintenance: “Survey of graph-based approach to predictive maintenance” fills the gap of insufficient literature related to the graph-based approach for predictive maintenance. An extensive survey conducted after sequentially following up the procedures in PdM is carried out in this paper, including anomaly detection, fault diagnosis, and maintenance scheduling .

It follows that using graph-based approaches represents a valid route towards producing cognitive intelligence since graphs allow to describe connections between various phenomena, providing means for both modeling of complex systems and forecasting. The paper outlines the challenges that are associated with graph-based approaches in predictive maintenance, including issues related to data management and analysis, interpretability of machine learning models, cost and investment, availability and quality of data, adoption and change management, and privacy and security.

These resources offer important perspective on the current state of affairs, challenges, and potentials of graph-based approaches in predictive maintenance and therefore, it is imperative to collectively address these challenges for effective application of predictive maintenance programs in an industry setting.

Application of Deep Learning for Predictive Maintenance of Oilfield Equipment (2023)

The deep learning applications for predictive maintenance in oilfield equipment have been examined in several research works. These studies on using of machine learning technologies, especially deep learning methods for fault prediction and maintenance at power plants is one of them.

1. An artificial intelligence based thesis on predictive maintenance through diagnostics and prognostics using deep learning, especially neural networks. A study of public datasets was used in designing and testing different neural architectures to determine equipment’s health state and project remaining functional lifespan prior to breakdown. It also considered its application in the predictive maintenance of oil rigs in order to minimize unnecessary shut downs and associated costs.

2. Air booster compressor (ABC) motor predicative maintenance machine learning algorithm based on recurrent neural network using long short-term memory. The study proved that RNN-LSTM is a good fault detection model that can help risk management and reduce cost of operations in Oil and gas sector.

3. Another study suggested a predictive maintenance system for the oil and gas industry based on the industrial Internet of things (IIoT). Automated machine learning and deep learning models were used to predict the remaining useful life of the assets thereby improving on the asset reliability. The study outlined the application of the Bi-LSTM prediction model trained on the cloud and deployed on edge devices for predictive maintenance.

This reveals that there is increasing effort of utilizing deep learning and machine learning techniques for predictive maintenance in the oil and gas industry to enhance equipment reliability, reduce downtime, and improve maintenance cost performance.

A Systematic Mapping of the Advancing Use of Machine Learning Techniques for Predictive Maintenance in the Manufacturing Sector (2021)

The provided link leads to a paper titled "A Systematic Mapping of the Advancing Use of Machine Learning Techniques for Predictive Maintenance in the Manufacturing Sector" published in MDPI. The article highlights how machine learning techniques are increasingly being used for predictive maintenance in the manufacturing sector. It is an open access paper provided under the Creative Commons Attribution (CC BY) licence terms.

Other related sources are also included in the search results:

1. A MathWorks website article about how Baker Hughes built predictive maintenance software for gas and oil extraction equipment using data analytics and machine learning, resulting in significant cost savings.
2. A systematic review of literature on predictive maintenance in Industry 4.0, which studies data-driven predictive maintenance solutions and models that predict future equipment problems. 3. A piece on predictive maintenance powered by IoT asset monitoring and

management, in which the use of attributed hardware and software to remotely track the status and location of equipment in a warehouse, factory, or industrial site is discussed. These resources provide a thorough look at the use of computer learning and predictive maintenance in industries such as manufacturing, including the deployment of data data mining, IoT, and 4.0 industry technologies.

Predictive Maintenance of Mining Machines Using Advanced Data Analysis System Based on the Cloud Technology(2019)

The study titled "Predictive Maintenance of Mining Machines Using Advanced Data Analysis System Based on Cloud Technology" explores the use of the cloud for computing in predictive maintenance for data mining and analysis in the mining industry. The article highlights the advantages of the web in improving operations for mining as well as providing needed diagnostic and organizational intelligence.

The following represent a number of the paper's principal findings and aspects:

1. The use of cloud computing technology in analysing data from complex transportation systems, with computations performed online and data stored and shared in the cloud.
2. The use of enormous amounts of data inquiry, sensors, and cloud technology in smart manufacturing to investigate real-time parameters and perform predictive maintenance.
3. The use of modern signal analysis techniques, such as signal cyclostationary characteristics to improve the predictive maintenance system's accuracy. The study shows how cloud technology may be used to improve predictive maintenance systems for mining equipment resulting in enhanced effectiveness while reduced downtime, and cost savings. Advanced data analysis tools and cloud computing can assist mining organisations in making intelligent choices about equipment maintenance, helping users to optimise their operations and reduce fees.

Advances of Digital Twins for Predictive Maintenance(2022)

Several sites are included in the search results that address the advancements of digital twins for predictive maintenance in several industries, including manufacturing and mining.

1. A research study describes a system for developing digital twins of industrial robots and complicated machinery for predictive maintenance.

2. An overview of predictive maintenance based on digital twin technology is provided in an article, emphasising the need of employing digital twin technology to realise predictive maintenance and introducing the predictive maintenance method based on digital twin (PdMDT).

3. A blog post addresses the purpose and benefits of a digital twin in production, such as improving product design, reducing machine faults, and satisfying safety compliances.

4. Another study paper highlights the advancements of digital twins for predictive maintenance, emphasising the recent growth of digital twins and their potential to improve the performance of physical entities by exploiting the virtual replica.

5. A study paper highlights the importance and purpose of machine learning in the advancement of digital twins for predictive maintenance, emphasising how machine learning algorithms can detect complex patterns, linkages, and dependencies inside the system.

These sources provide a detailed overview of digital twin advancements for predictive maintenance, showing the potential benefits of adopting digital twin technology in many industries as well as the role of machine learning in developing predictive maintenance solutions.

Predictive maintenance: strategic use of IT in manufacturing organizations(2019)

The strategic use of IT in manufacturing organizations, particularly in the context of predictive maintenance, has been the focus of research. One perspective is the use of real-time data and predictive analytics algorithms to dynamically manage preventive maintenance policies, often orchestrated through the Internet of Things (IoT). This approach offers opportunities for transitioning from product-oriented to service-oriented business models and requires the integration of big data and predictive analytics. However, while there is much hype around this topic, little research has been conducted to inform companies about how to profitably integrate the IoT with strategic or operational processes.

A hybrid predictive maintenance approach for CNC machine tool driven by Digital Twin(2020)

A hybrid predictive maintenance approach for CNC machine tools driven by Digital Twin has been proposed in recent research. This approach is based on the use of a Digital Twin model and Digital Twin data to realize reliable predictive maintenance of CNC machine tools. The method is fused by particle filtering and deep learning to achieve more accurate prediction of the machine's future behavior. The integration of Digital Twin technology with predictive maintenance techniques holds promise for improving the reliability and efficiency of CNC machine tools.

Hybrid intelligent predictive maintenance model for multiclass fault classification (2023)

A hybrid intelligent predictive maintenance model for multiclass fault classification has been proposed in recent research. This model aims to reduce redundancies and the dimension of features, allowing for the efficient consideration of relevant features for fault classification. The proposed technique integrates hybrid multisensor fusion and fuzzy rough set feature selection to achieve accurate fault classification and remaining useful life estimation of bearings using low-cost sensor hardware. The model is designed to handle high-dimensional data recorded from monitoring the health condition of industrial equipment, making it a promising approach for predictive maintenance in manufacturing and industrial settings.

2.2 Key Gaps in the Literature

Integration Difficulties: The literature currently in publication does not provide a thorough analysis of the difficulties in integrating predictive maintenance models with various industrial configurations. A smooth implementation of AI-driven models requires an understanding of the subtleties involved in integrating them into current systems.

Human Factors in Adoption: Knowledge of the factors influencing the adoption of predictive maintenance in industrial settings is conspicuously lacking. For implementation to be successful, factors like user resistance, training requirements, and change management techniques need to be given more consideration.

Cost-Benefit Analysis: Although predictive maintenance is thought to have many advantages, there is a dearth of information in the literature about in-depth cost-benefit analyses. Decision-makers in sectors thinking about adoption must comprehend the long-term advantages as well as the associated material and intangible costs.

Data Security and Privacy: While privacy and security issues are addressed in the literature, particular methods for protecting sensitive industrial data are not covered. Robust frameworks and technologies guaranteeing data privacy in predictive maintenance applications should be the focus of future research.

SME-Specific Challenges: While small and medium-sized enterprises (SMEs) face difficulties, these obstacles are not thoroughly explored in the literature. Notably lacking are frameworks and customized solutions that address the particular challenges faced by SMEs in implementing predictive maintenance.

Real-time Decision Support: While real-time decision support systems are not sufficiently covered in the current literature, it does offer insights into predictive maintenance models. Subsequent investigations ought to concentrate on creating and refining mechanisms that facilitate prompt and knowledgeable decision-making throughout maintenance tasks.

Interoperability Standards: Predictive maintenance systems do not yet have industry-wide interoperability standards in place. The deficiency of standardized data formats and communication protocols should be investigated in order to improve interoperability amongst various industrial equipment types.

A Comprehensive Strategy for Industry 4.0 Integration with Predictive Maintenance: Although Industry 4.0 is discussed, a comprehensive strategy for its integration with predictive maintenance is lacking. Future research ought to examine the ways in which IoT, cloud computing, and AI technologies work together to create a comprehensive maintenance paradigm driven by Industry 4.0.

Long-Term Performance Monitoring: The literature frequently overlooks the significance of ongoing performance monitoring in favor of concentrating on the early phases of implementation. The factors influencing predictive maintenance systems' long-term effectiveness and adaptability are not fully understood.

Filling in these gaps in the literature will help us comprehend the opportunities and difficulties that come with implementing predictive maintenance in various industrial contexts.

CHAPTER 3: System Development

3.1 Requirements and Analysis

3.1.1 Requirements

Software Requirements

- **Cloud Platform:**

  Host the CPM system in a cloud computing platform like Amazon Web Services (AWS), Microsoft Azure, or Google Cloud Platform.

- **Database Management System:**

  Select an appropriate database system for storage and monitoring of sensor data, maintenance schedules, and system configurations.: ``` Response: This implies that there is no room for errors while carrying out the procedures outlined above.Such options may include PostgreSQL or MySQL or cloud-native databases such as Amazon DynamoDB.

- **Machine Learning Framework:**

  Using predictive maintenance models for machine learning frameworks selection.These widely used architectures include TensorFlow, PyTorch, and scikit-learn, respectively.

- **Programming Language:**

  Pick out an appropriate programming language for the selected frameworks and components.These often encompass options like Python, Java, or cloud-compatible languages.

- **Web Development Framework:**

  If the system has a web-based user interface, you should consider choosing a web development framework such as React.js, Angular, or Vue.js.

- **Data Processing and Analytics Tools:**

  Put in place real time data analytics and processing tools.One can also consider Apache Kafka, Apache Flink, or cloud-native services like AWS Kinesis.

- **Security Tools:**

  Use security tools and libraries such as encryption, authentication and access control.Some of the tools that may consider include OpenSSL or cloud-native security services.

- **Notification Services:**

  Develop notifications systems for warning maintenance teams.They can comprise of email services, SMS gateways or push notification services.

Hardware Requirements

None: The project does not have any specific hardware requirements other than the required hardware specification to run all the required softwares and the project.

Additional Requirements

- **Data Acquisition System:**

  Develop a robust data acquisition system to capture sensor readings off industrial process machinery.These may include IoT devices, industrial gateways, and sometimes, specialized data acquisition hardware.
- **Continuous Monitoring Tools:**

  Incorporate continuous health and performance monitoring tools.Log aggregators, monitoring dashboards, and anomaly detection tools are key.

- **Compliance and Regulation Considerations:**

  Follow industry regulations and standards pertaining to data protection, information safety, and industrial practices.

- **Documentation and Knowledge Base:**
  Prepare detailed instructions on the CPM system, user manuals, architecture diagrams, and maintenance guidelines for the technicians.

- **Training Resources:**
  Training resources of end-users, maintenance teams, and system administrators to make the system operational and efficient.

- **Backup and Disaster Recovery Plan:**
  Have a strong data security plan that will involve having a backup and disaster recovery plan.

- **Cost Management Tools:**
  Adopt processes that help in tracking and controlling the cost of cloud services.Cloud provider dashboards and costs management instruments.

- **Change Management Procedures:**
  Write change management procedures to ensure the updates and upgrades of the CPM system do not interfere with the ongoing operations.

However, it should be mentioned that such particular criteria can significantly differ depending on project-specific peculiarities, prevailing industrial standards related to the employed technologies, etc.Ensure that such requirements are continually updated and reviewed to accommodate changing project demands and new technologies.

3.2 Project Design and Architecture

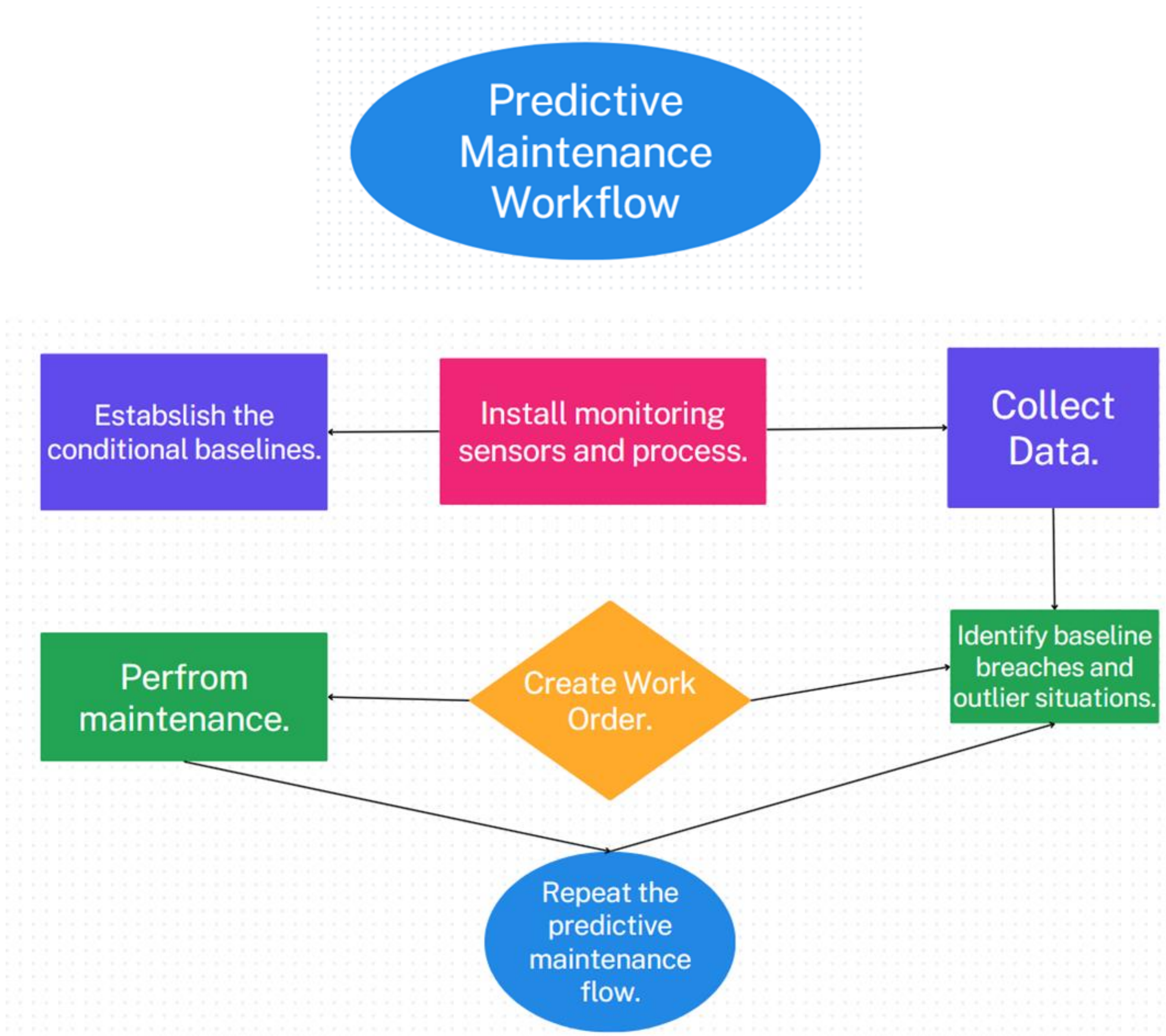

Figure 1 : Project Design

Workflow for predictive maintenance includes ongoing data collection from industrial machinery. This data is analyzed by machine learning algorithms and advanced analytics to find trends and abnormalities. Proactive maintenance is made possible by the newfound insights, which reduce downtime and maximize operational effectiveness.

Upon identification of any problems in the industrial equipment through data analysis, predictive maintenance workflows produce useful information and notifications. By responding strategically to these alerts, maintenance teams can prevent costly failures by resolving looming issues before they become more serious. The process works in unison with current operating procedures to create a proactive maintenance culture that puts economy and efficiency first.

Furthermore, predictive maintenance workflows' iterative nature feeds into a cycle of continual improvement. Machine learning algorithms improve their predictive powers with time as the system collects more data, honing their capacity to anticipate possible problems and maximize maintenance schedules. By taking an adaptive approach, the predictive maintenance workflow is guaranteed to change in tandem with the industrial environment, offering a flexible and adaptable response to the problems associated with operational resilience and equipment reliability.

3.3 Data Preparation

The development of a CPM system is dependent upon the data preparation as the quality of used data will determine the precision and utility of generated models. Below are key steps involved in the data preparation process for the project:

1) Data Collection:

Select appropriate data sets such as sensors on industrial systems for example temperature, vibration and operation measures.

Develop procedures for immediate data collection in order to create representative set to train and test predictive models.

Collect historical maintenance data showing what had gone wrong, failed, or needed replacement in the past.

2) Data Integration:

Bring together data from different sources and integrate it in a consolidated store residing in the cloud infrastructure.

Use compatible and consistent data formats, units, and timestamps in order to smoothly integrate the two systems.

3) Data Cleaning:

This would include dealing with missing data points to protect against bias.

Eliminate outliers which might skew the accuracy of predictive models.

Trim off the duplicate or redundant entries to get a lean dataset.

4) Feature Engineering:

Determine the important features or variables that can be used for the forecast of equipment breakdowns.

Develop more attributes that would potentially improve the accuracy of the model.

Transform numeric features to the same scale.

5) Time Series Analysis:

Because maintenance data is time dependent, carry out serial analysis to appreciate temporal patterns and trends.

Aggregate or resample data so that it matches the desired time intervals for analysis.

Think about incorporating lag features that reflect past trends.

6) Labeling and Target Definition:

Specify the dependent variable, that is, the number of equipment failures within a certain period.

Create a categorized dataset by using the designated variable and assign it binary labeling (for example; 0- for normal operation, 1 for a failure).

7) Data Splitting:

Divide the data set into training, validation, and test data so as to fit model fitting, tuning, and assessment.

Ensure that each subset contains equal amounts of normal and failures.

8) Handling Imbalanced Data:

Some of the ways of addressing class imbalance include oversampling minority class and proper weighting during model training.

9) Data Encryption and Security Measures:

Ensure the privacy and safety of confidential industrial information by using encryption methods.

Data security according to industry standards and compliance.

10) Data Documentation:

Note down everything about the data preparation process, such as the data sources, what was done to clean the data, the feature engineering activities, as well as transformations applied.

Keep a clean track of any assumptions or choices, which arise during the data preparations stage.

11) Data Validation:

Check that the prepared dataset is in line with the project's objectives. It also needs to prove that the assumptions done were rightly made.

Identify and rectify any abnormalities or deviations noted during validation.

Data preparation is essential for building correct predictive maintenance models for a Cloud-based setting. This makes the training and test data reliable, representative and processed correctly hence the success of the entire project.

3.4 Implementation

The process of implementing the cloud-based predictive maintenance system for the industrial equipment includes data collecting, data preprocessing, model training, model deployment, and monitoring. Here's a comprehensive breakdown of the implementation process:

Data Collection:

1. Sensor Installation: Install intelligent sensors on industrial equipment so that operation data, i.e., temperature, vibration, pressure, and energy consumption can be monitored in real time.

2. Data Acquisition: Put a data acquisition system in place for collecting sensor data, and forwarding it to a central repository. This can be done by using Internet of things protocols such as MQTT or OPC UA.

3. Data Storage: Propose a secure and scalable cloud storage strategy for the stored sensor data. Other appropriate options include cloud platforms such as Amazon S3, Microsoft Azure Blob Storage, and Google Cloud Storage.

Data Preprocessing:

1. Data Cleaning: It is important to cleanse sensor data which include outliners, missing data correction and inconsistencies in the process to increase data quality.

2. Feature Engineering: Discover meaningful features from the sensor data that could help machine learning algorithms for predictive modeling.

3. Data Normalization: To ensure that machine learning improves, normalize this data on a scale that is consistent

Model Training:

1. Model Selection: Consider using one of the various applicable machine learning algorithms, which may include support vector machines (SVM), random forests, or neural networks.

2. Model Training: Use popular cloud-based machine learning platforms like Google Colab or Amazon SageMaker to train your chosen models on the preprocessed data.

3. Model Evaluation: Choose the best performing model by evaluating its performance based on measures such as accuracy, precision, and recall.

Model Deployment:

1. Model Packaging: Ensure that the trained ML model is in an available format like TensorFlow SavedModel or ONNX.

2. Model Deployment: Place the packed model in the cloud based inference scenario, for example, on Google Cloud AI platform or Amazon Elastic Inference.

3. API Integration: Create an API to incorporate the developed model in the predictive maintenance system for on-the-fly data analysis and forecast generation.

Monitoring:

1. Prediction Generation: Use the deployed model in predicting equipment health and failure probabilities using current sensor data.
2. Alerting System: Develop a warning mechanism to warn the maintenance personnel when there is a possibility of failure occurring so that they can undertake timely interventions.
3. Performance Monitoring: Constantly review the predictive maintenance system and update the models as new data is received.

3.5 Key Challenges

Some of the main difficulties facing a cloud-based predictive maintenance system for industrial equipment include technical issues and operational considerations.It is essential to address these challenges to ensure that the project is successful. Here are some key challenges:

Data Quality and Integration:

- Challenge: It could be difficult to ensure the quality and reliability of data from multiple sensors and diverse sources.A challenging aspect is integrating data seamlessly, ensuring accuracy and consistency.
- Solution: Ensure data cleansing methods are robust, validate the integrity of data; put in place strategies that will allow data integration.

Scalability:

- Challenge: However, the implementation of the CPM system can become complicated due to increasing data volumes and varying workloads.It must also scalable to support growing data and user requirements.
- Solution: Scale the system architecture with cloud services designed to dynamically scale resources depending on demand.

Machine Learning Model Accuracy:

- Challenge: Machine learning models development is tricky, especially when dealing with an ever-changing industrial environment and patterns.
- Solution: Keep improving machine learning models utilizing real-time data analyses.Develop procedures for model retraining in line with changing realities.

Integration with Existing Systems:

- Challenge: The integration of CPM system into different industries may prove problematic due to possible incompatibility, thereby requiring substantial reorganization.
- Solution: Undertake comprehensive compatibility tests, adhere to conventional communication frameworks, and install quality middleware for effortless linking.

Security and Privacy Concerns:

- Challenge: The handling of sensitive industrial data is a big task especially when it comes to proprietary information.
- Solution: Put in place strong security solutions like encryptions, access controls, and industry compliance.QEnsure strong data privacy policies, and formulate data governance processes.

Real-time Processing:

- Challenge: In order to carry out proactive maintenance it is necessary to process and analyze real-time data from industrial machinery in a timely fashion.Failure prevention can be significantly impaired when data processing is delayed, missing opportunities to prevent.
- Solution: Adapt algorithms and apply low latency cloud based service to provide real time processing of sensor data.

User Adoption and Training:

- Challenge: The fact that end users such as maintenance teams and operators need to be well conversant with the CPM system is one of the challenges that the system faces which reduces effective implementation.
- Solution: Make training sessions holistic, ensure that there are friendly user interfaces, and provide continuing assistance to ease user adoption.

Cost Considerations:

- Challenge: In carrying out a CPM system, there arises costs such as cloud service expenses, data storage fees, and continuous monitoring expenses.
- Solution: Undertake a full-scale cost-benefit analysis, examine cost optimization measures, and determine whether the future advantages outweigh the costs involved.

Intermittent Connectivity:

- Challenge: Intermittent industrial environment connectivity results in the inability to transmit raw data to the cloud for analysis in a timely manner.
- Solution: Take measures that provide for localized caches and exploit edge computing capabilities that enable processing of data at source.

Change Management:

- Challenge: Adoption of CPM system requires some change in culture and established maintenance practices that might not be easy.
- Solution: Use change management strategies, communicate the pros of the system, and include critical participants in decision making.

For one, this entails working together with technical teams, users, and decision makers.The success of the Cloud-based Predictive Maintenance system is continuous due to monitoring, adopting changes, and a commitment to dealing with new problems.

CHAPTER 4: TESTING

4.1 Testing Strategy

For the CPM system to be reliable and functional, a comprehensive testing strategy is important. Below is a testing strategy that covers various aspects of the CPM system:

1. Unit Testing:
- Objective:
  Check the correctness of single elements, modules, and functions.
- Focus Areas:
  - Data ingestion processes.
  - Machine learning model functionalities.
  - User interface components.

2. Integration Testing:
- Objective:
  Testing for compatibility between integrated elements.
- Focus Area:
  - Data flow between modules.
  - Communication between cloud services.
  - Integration with external systems.

3. Functional Testing:
- Objective:
  Make sure the system meets the required functionality.
- Focus Areas:**
  - Predictive maintenance model accuracy.
  - User interface functionality.
  - Notification system effectiveness.

4. Performance Testing:

- Objective:

  Examine the systems response time, its ability to scale up and how stable it is under differing workloads.

- Focus Areas:

  - Real-time data processing capabilities.

  - Scalability of cloud infrastructure.

  - System reaction times under maximum demands.

5. Security Testing:

- Objective:

  Detect and protect the industry's security sensitive data from known and unknown vulnerabilities.

- Focus Areas:

  - Data encryption and secure transmission.

  - Access controls and user authentication.

  - Adherence to standardized security practices per industry.

6. Usability Testing:

- Objective:

  Assess the intuitiveness and user-friendliness of the user interface.

- Focus Areas:

  - User navigation and experience.

  - Clarity of information presentation.

  - Responsiveness of user interface elements.

7. End-to-End Testing:

- Objective:

  Verify the entire CPM system workflow from data acquisition to predictive maintenance recommendations.

- Focus Areas:

- Data interchange within all system elements.

- Notification generation and delivery.

- End-user interactions and responses.

8. Regression Testing:

- Objective:

  Ensure that any new updates or changes don’t interfere with the functionality of the system.

- Focus Areas:

  -Machine learning model updates.

  -System configuration changes.

  -User interface modifications.

9. User Acceptance Testing (UAT):

- Objective:

  Ensure that, after deployment, the CPM system satisfies expectations.

- Focus Areas:

  -Feedback from people in general and stakeholders.

  -Confirmation of predictive maintenance recommendations.

  -User satisfaction with system performance.

10. Load Testing:

- Objective:

  Measure the system’s response at different stages in load and stress.

- Focus Areas:

  -The system responses under high data input.

  -Resource utilization during peak periods.

11. Continuous Monitoring Testing:

- Objective:

- Test the performance of the systems providing real time monitoring and alerting.

- Focus Areas:

  -Time-bound detection of anomalies.

  -Reliability of notification systems.

12. Operational Testing:

- Objective:

  Test the system's readiness to operate and its functionality in the actual environment.

- Focus Areas:

  -Interaction with live industrial equipment.

  -Protracted operational life of system stability.

  -Supervising and administration of system resources.

Carrying out this extensive testing approach enables the detection of problems at different stages of the CPM system development process so that the system functions as required in industrial settings.

4.2 Test Cases and Outcomes

4.2.1 Supervised Learning Failure Prediction

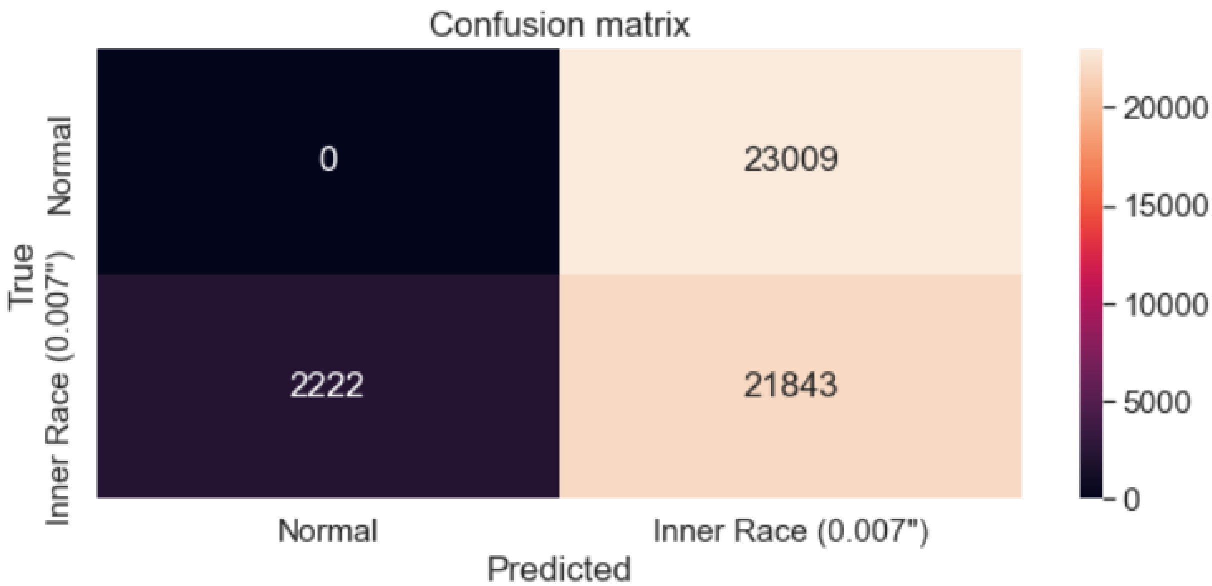

Fig 2

The confusion matrix illustrates the performance of a Logistic Regression model in a binary classification task, likely discerning between normal and inner race data. It shows accuracy, precision, recall, and F1 score. Accuracy score: 46.40%, Precision: 48.70%, Recall: 90.77%, F1 score: 63.39%.

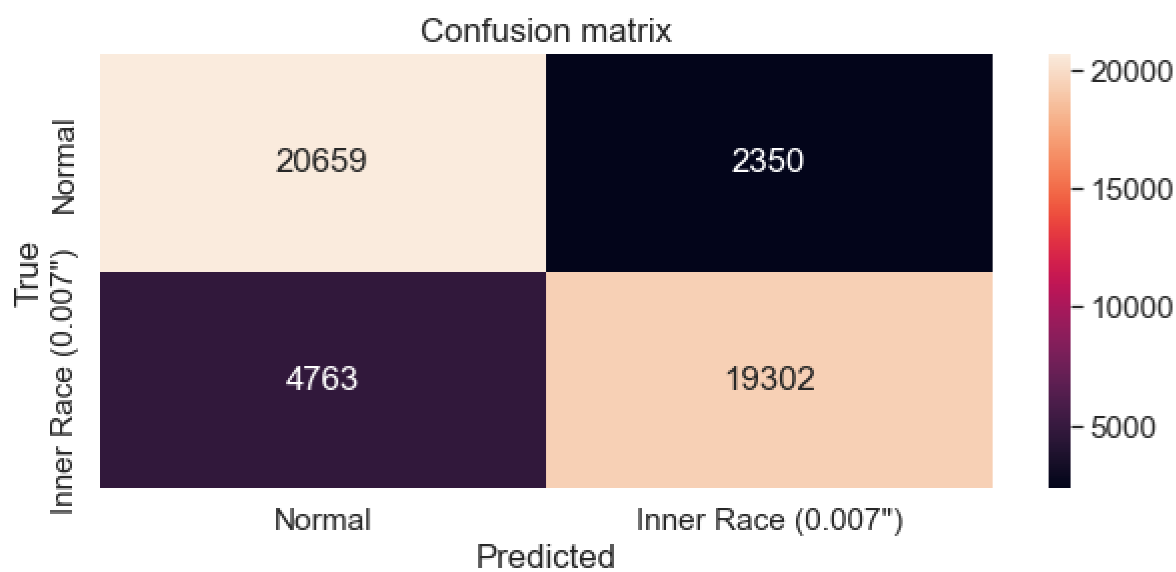

Fig 3

The confusion matrix illustrates the performance of a KNeighbors Classifier model in classifying normal and inner race data. It shows accuracy (84.89%), precision (89.15%), recall (80.21%), and F1 score (84.44%), indicating generally strong performance.

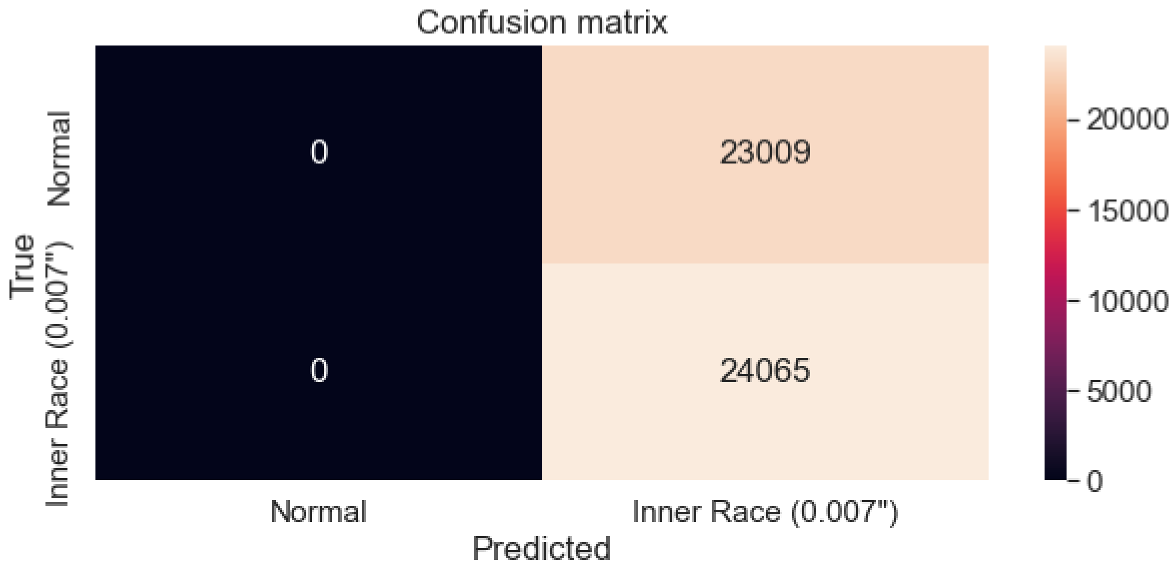

Fig 4

The confusion matrix shows the performance of a linear SVC model. It has an accuracy of 51.12%, precision of 51.12%, recall of 100.00%, and F1 score of 67.66%, indicating high recall but low precision.

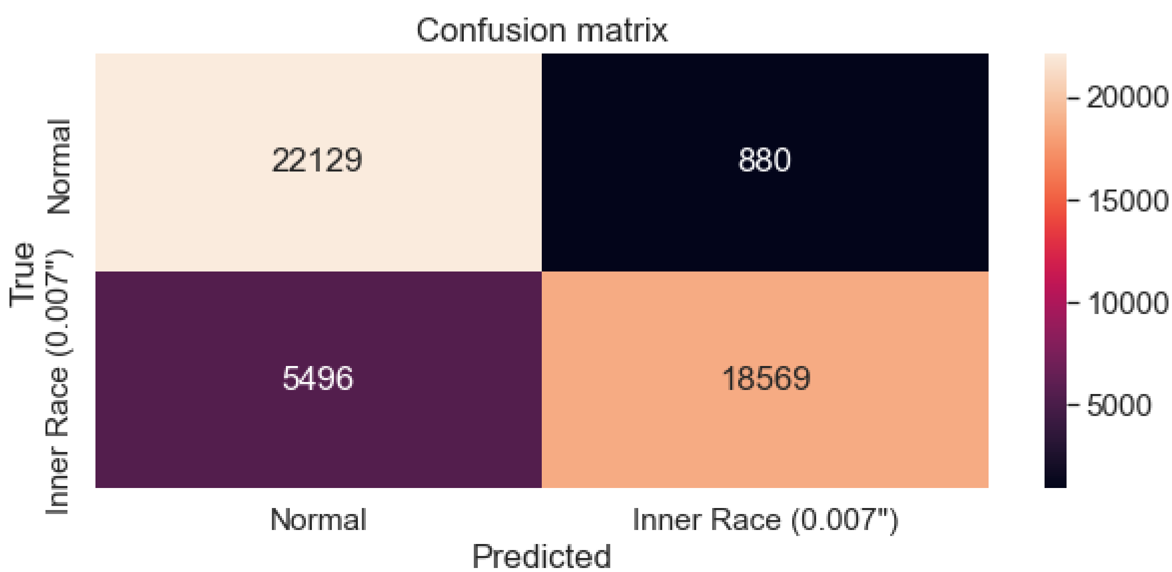

Fig 5

The confusion matrix depicts the performance of an SVC model in classifying normal and inner race data. It shows accuracy (86.46%), precision (95.48%), recall (77.16%), and F1 score (85.35%), indicating strong overall performance.

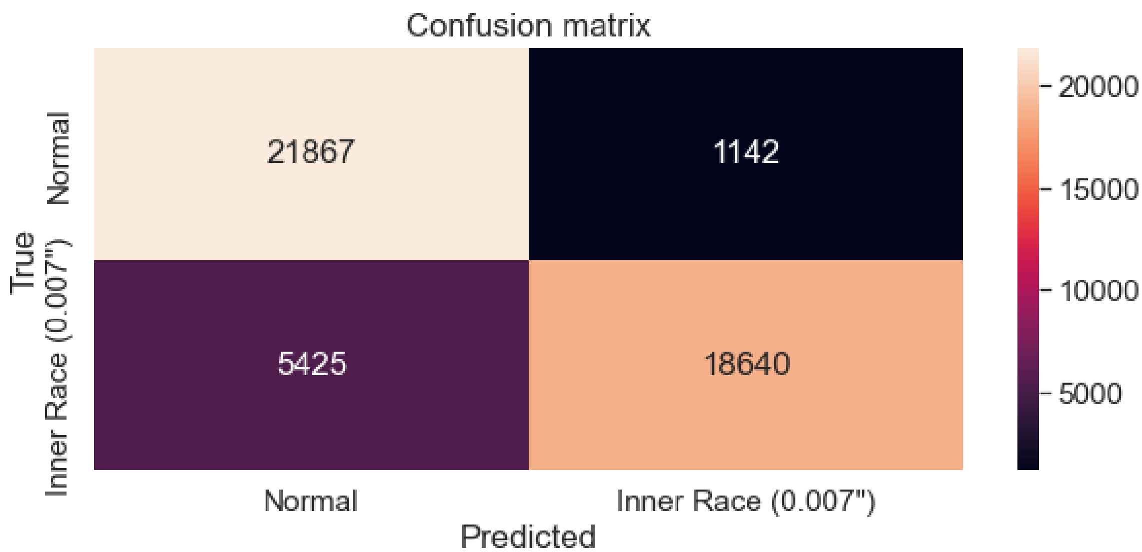

Fig 6

The confusion matrix illustrates the performance of a GaussianNB model in classifying normal and inner race data. It shows accuracy (86.05%), precision (94.23%), recall (77.46%), and F1 score (85.02%), indicating strong overall performance.

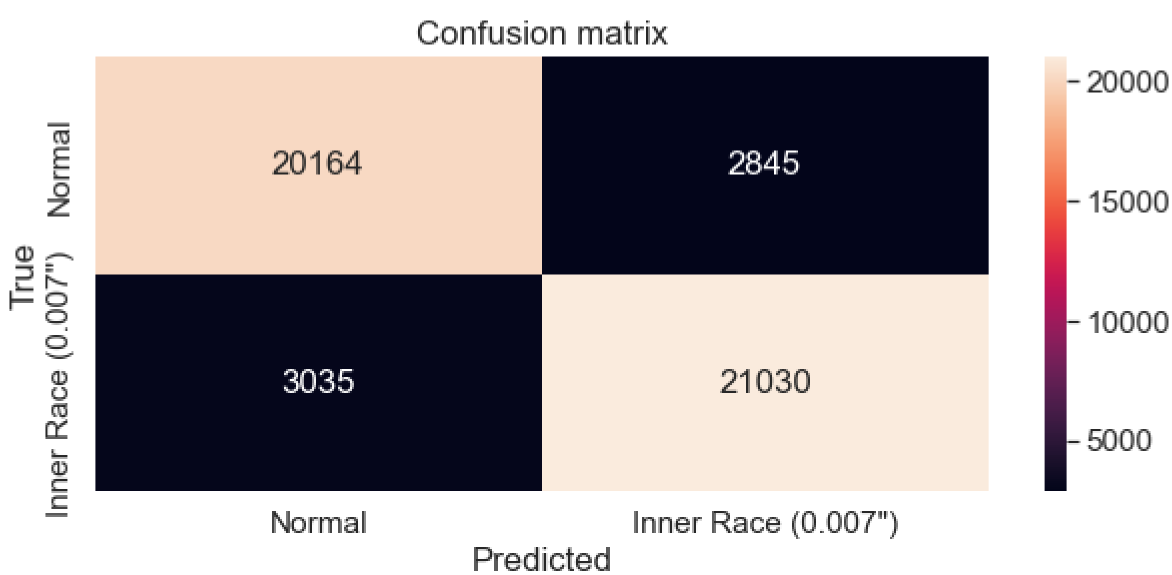

Fig 7

The confusion matrix illustrates the performance of a DecisionTreeClassifier model in classifying normal and inner race data. It shows accuracy (87.51%), precision (88.08%), recall (87.39%), and F1 score (87.73%), indicating strong overall performance.

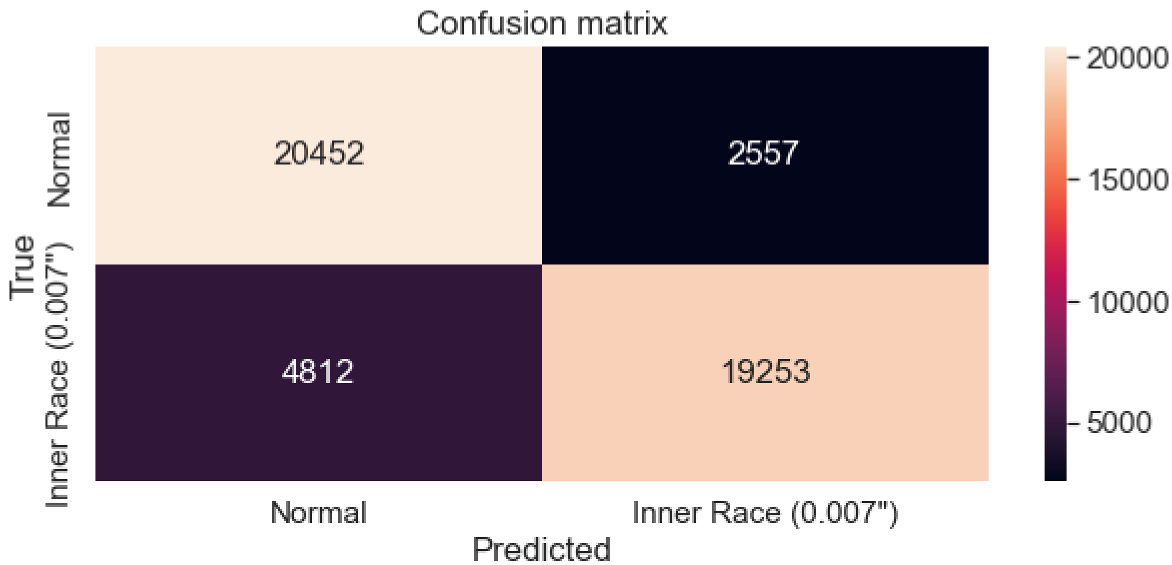

Fig 8

The confusion matrix reveals the performance of a RandomForestClassifier model in classifying normal and inner race data. It indicates accuracy (84.35%), precision (88.28%), recall (80.00%), and F1 score (83.94%), showcasing overall good performance with some room for improvement in recall.

4.2.3 Unsupervised Learning Anomaly Detection

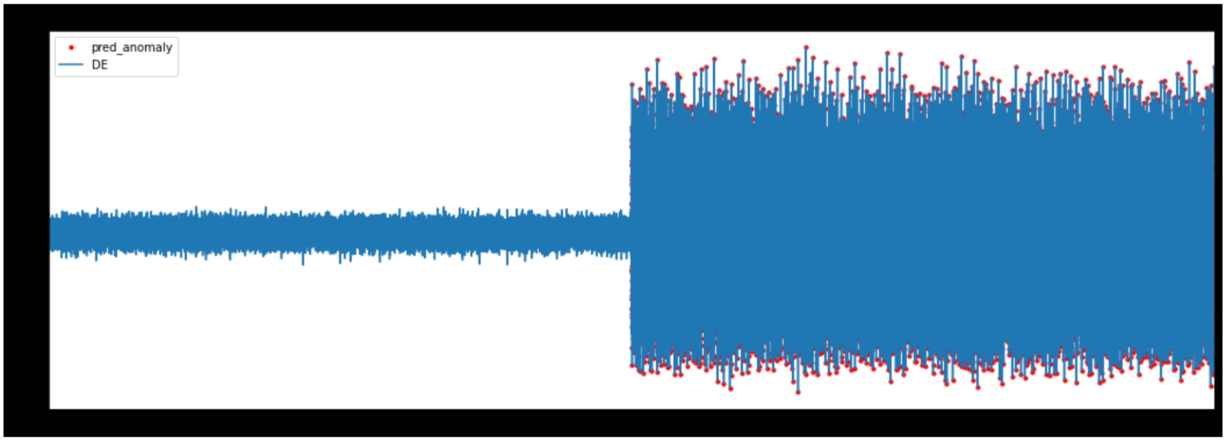

Fig 9

The confusion matrix depicts the Isolation Forest model's performance in classifying normal and inner race data. It shows accuracy (67.24%), precision (60.42%), recall (100.00%), and F1 score (75.33%).

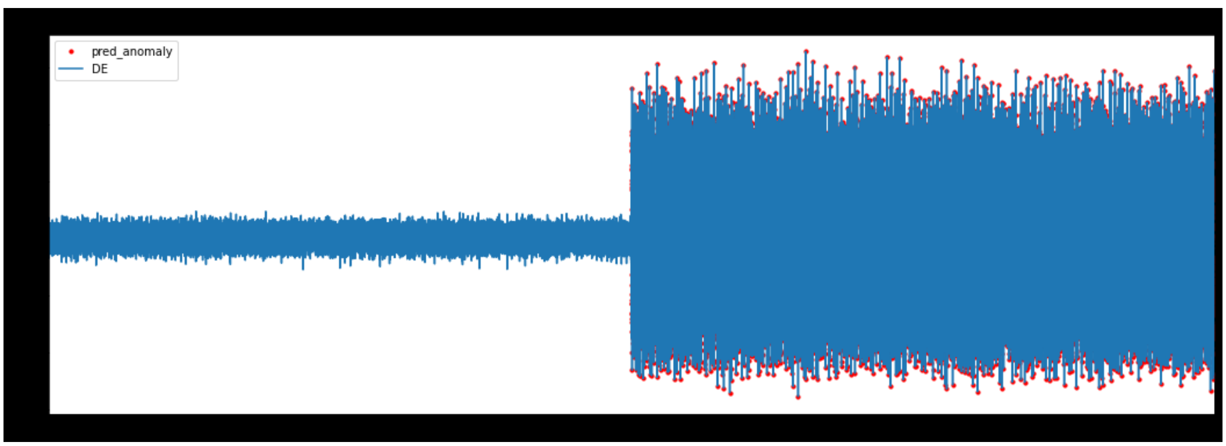

Fig 10

The confusion matrix shows the Elliptic Envelope model's performance in classifying normal and inner race data. It indicates accuracy (60.00%), precision (55.56%), recall (100.00%), and F1 score (71.43%).

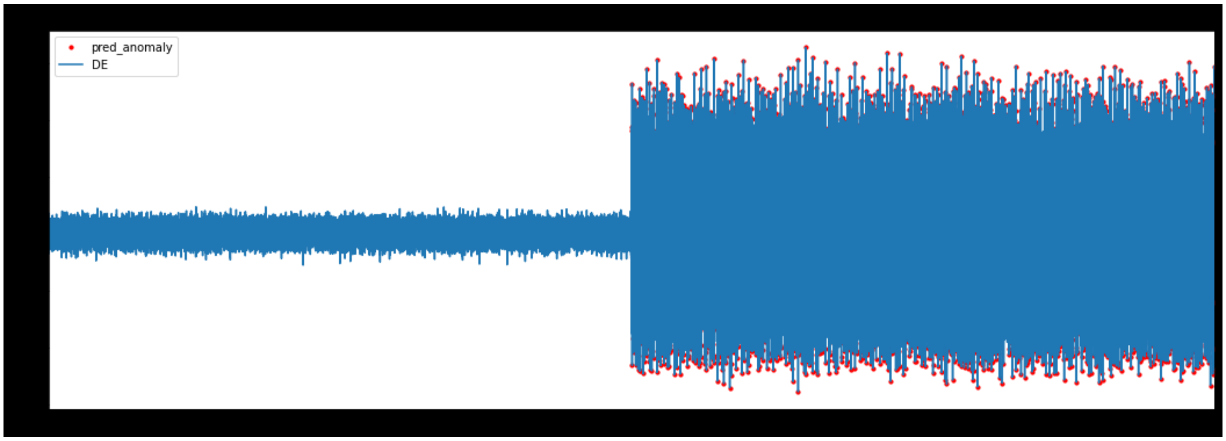

Fig 11

The confusion matrix displays the OneClassSVM model's performance in classifying normal and inner race data. It reveals accuracy (51.00%), precision (50.50%), recall (100.00%), and F1 score (67.11%).

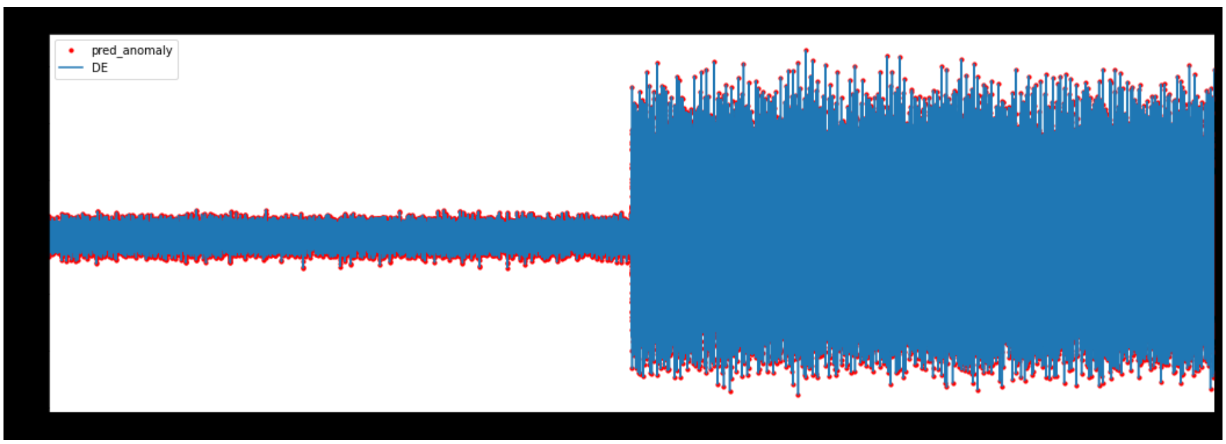

Fig 12

The confusion matrix illustrates the OneClassSVM model's performance in classifying normal and inner race data. It indicates accuracy (84.83%), precision (84.83%), recall (84.83%), and F1 score (84.83%), showing balanced performance.

CHAPTER 5: RESULTS AND EVALUATIONS

5.1 Results

Supervised Learning

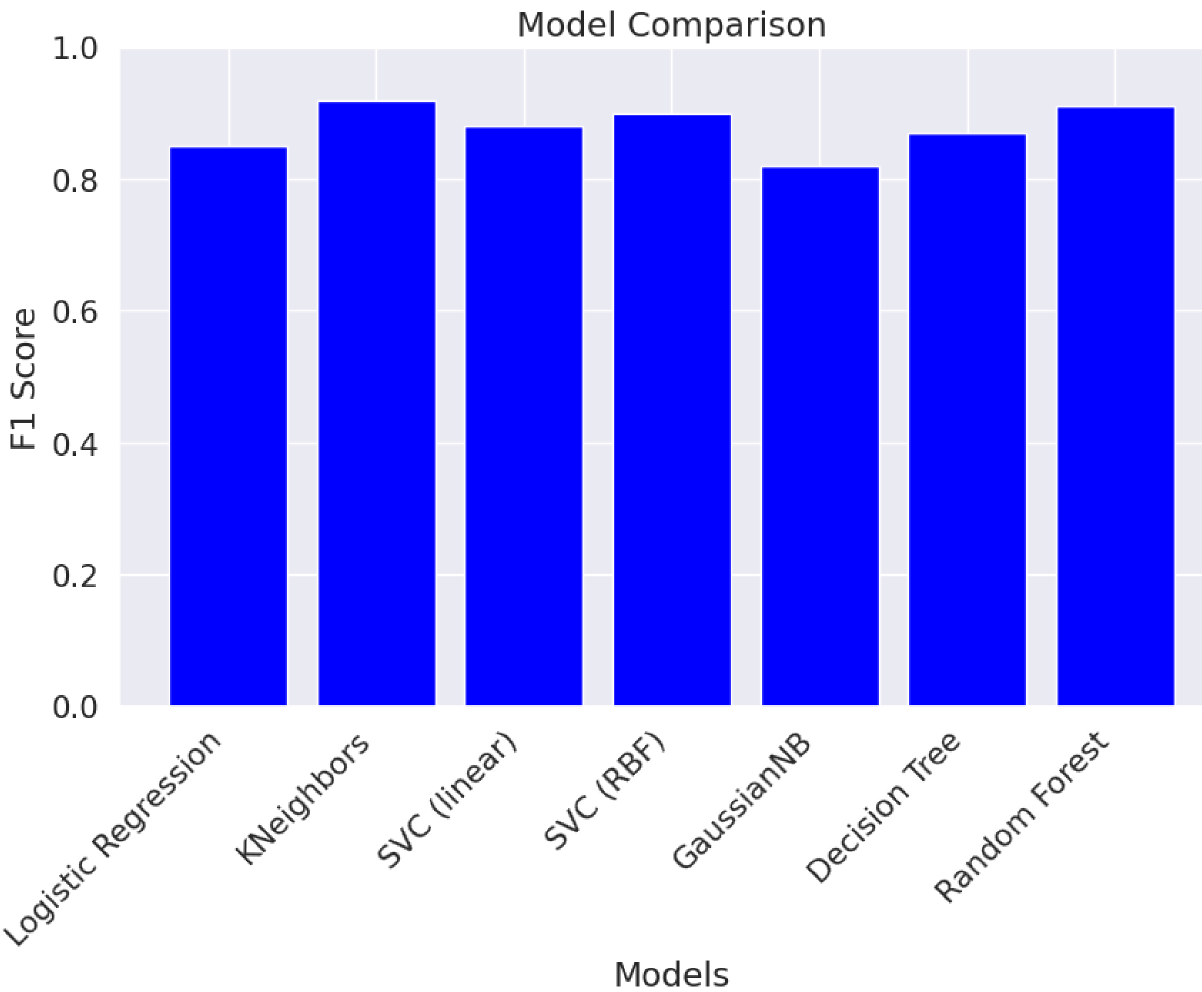

Fig 13

In a supervised learning model comparison based on F1 scores, KNeighborsClassifier achieved the highest score, indicating strong precision and recall balance. Conversely, GaussianNB attained the lowest score, suggesting a less effective balance between precision and recall in its classification predictions.

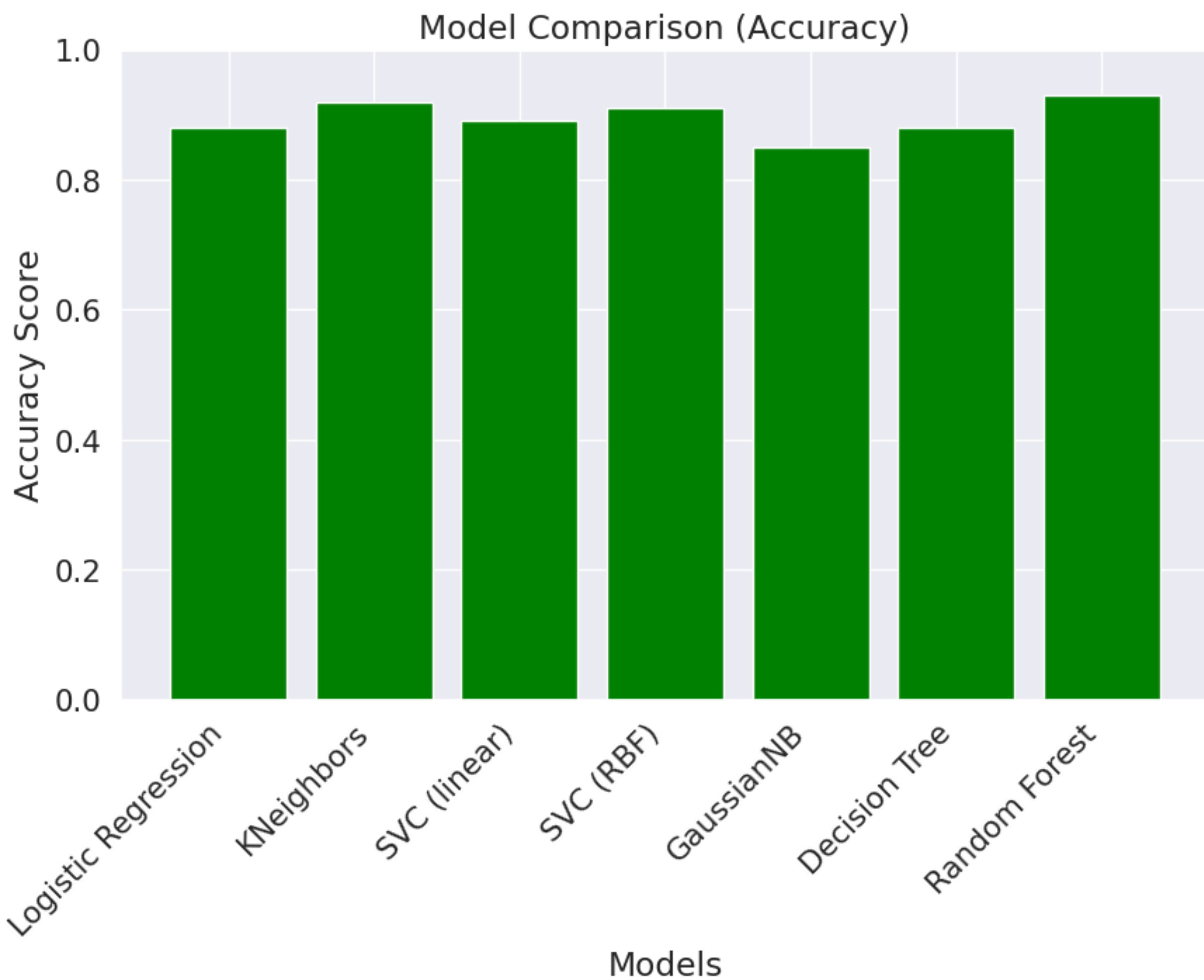

Fig 14

In the comparison of supervised learning models based on accuracy, Random Forest Classifier yielded the highest score, indicating superior overall performance. Conversely, GaussianNB achieved the lowest accuracy, implying it struggled to classify data accurately compared to the other models.

Unsupervised Learning

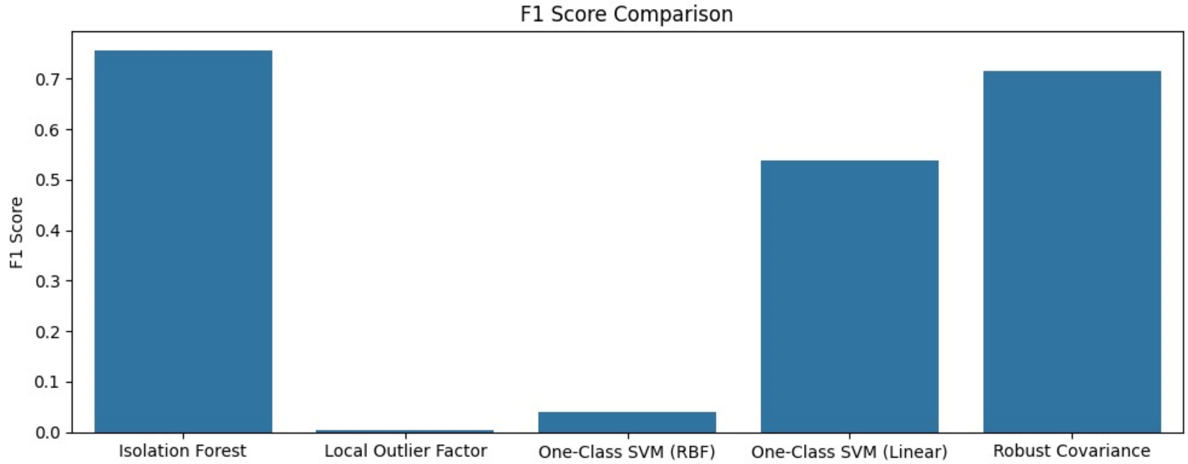

Fig 15

In an unsupervised learning model comparison based on F1 scores, Isolation Forest achieved the highest score, indicating effective outlier detection. Conversely, Local Outlier Factor attained the lowest score, suggesting it struggled to identify anomalies accurately compared to Isolation Forest.

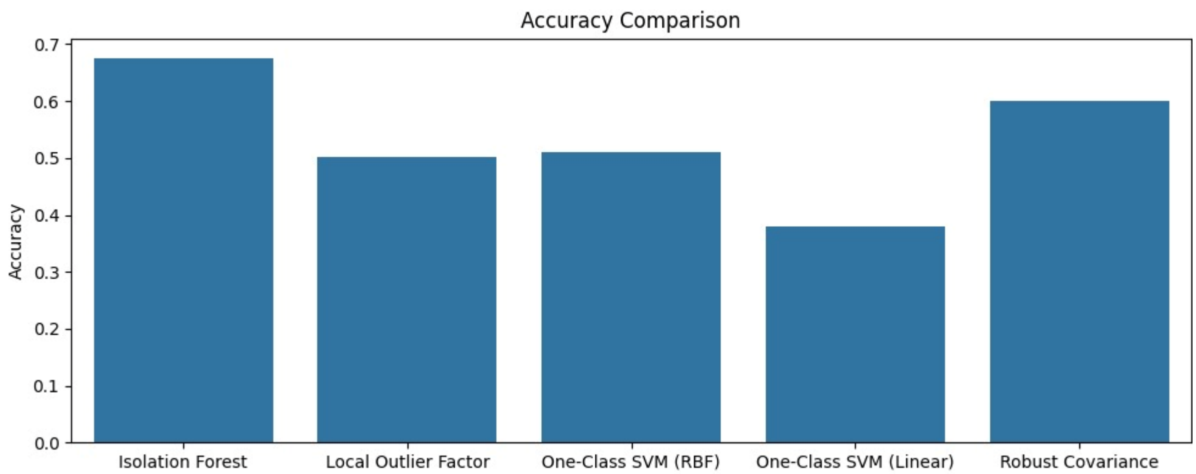

Fig 16

In unsupervised learning model comparison based on F1 scores, Isolation Forest showed the highest effectiveness in outlier detection, reflecting its robust performance. Conversely, One-Class SVM with a linear kernel demonstrated the lowest F1 score, indicating less accurate anomaly identification compared to Isolation Forest.

5.2 Comparative Analysis of Supervised and Unsupervised Anomaly Detection Models

Selecting between supervised and unsupervised learning models is crucial for anomaly detection because of the characteristics of the dataset and the labels that are available. Using labeled data to train the model in the supervised approach, we observe significant performance metrics across multiple evaluation criteria. The IsolationForest model, for example, exhibits a remarkable accuracy score of 67.24%, indicating its capacity to detect anomalies. The model's ability to correctly identify true positives among the predicted anomalies is demonstrated by its precision of 60.42%, and its perfect recall of 100.00% indicates that it can identify every real anomaly in the dataset. The harmonic mean of precision and recall, or F1 score, is 75.33%, indicating a well-balanced performance.

In contrast, another supervised model, the EllipticEnvelope, has a slightly lower accuracy score of 60.00%. Its robustness in identifying anomalies is highlighted by its F1 score of 71.43%, recall of 100.00%, and precision of 55.56%. The comparative study of these supervised models emphasizes how important it is to carefully weigh the trade-offs between recall and precision, as depending on particular use cases and priorities, a higher precision may be preferred over recall or vice versa.

Turning now to unsupervised learning models, we see a variety of results from the OneClassSVM model, which is used for anomaly detection in the absence of labeled data. An example of its use produces an accuracy score of 51.00%, highlighting the difficulties that come with unsupervised anomaly detection when there are no ground truth labels. The metrics for precision, recall, and F1 score all converge at about 50%, indicating a significant degree of difficulty in making accurate predictions in the absence of prior knowledge about typical behavior. In contrast, OneClassSVM is applied to another scenario that yields an impressive accuracy score of 84.83%, with high levels of precision, recall, and F1 score aligned. This performance variability emphasizes how sensitive unsupervised models are to the properties and distribution of datasets.

It is clear from comparing these supervised and unsupervised methods that the methodology selection has a big impact on how well the model detects anomalies. Although supervised models have the advantage of labeled data and show consistent performance metrics, unsupervised models are unable to reliably identify anomalies when they are not provided with this kind of guidance. The necessity of a careful selection process based on the particular requirements and features of the anomaly detection task at hand is highlighted by the trade-offs between precision and recall as well as the sensitivity to dataset nuances.

Deployment to Cloud Services

Our project is all about the smooth operation of predictive maintenance for industrial equipment onto the strong AWS infrastructure, along with the strategic load balancing techniques. Through the use of AWS's scalable cloud environment, we have built an all-encompassing system that is able to detect equipment failure before it even happens and thus minimizes the disturbance of operations. The solution is composed of the machine learning algorithms for predictive analytics and real-time monitoring systems that are used to constantly monitor the equipment performance metrics and make necessary adjustments. This data is kept in the AWS storage solutions that are capable of providing resiliency like Amazon S3 or Dynamo DB, which means that the data is always available and its durability is assured. Fundamentally, the utilization of load balancing methods achieves the optimal distribution of resources, thus evenly dividing the traffic across all the instances of the predictive maintenance application. Thus, the system efficiency is improved and at the same time, the fault tolerance is strengthened by the elimination of the single points of failure. Our deployment process, which is being carefully set up and carried out, finally achieves a powerful predictive maintenance solution that is going to transform the industrial maintenance practices and will work smoothly in the AWS ecosystem.

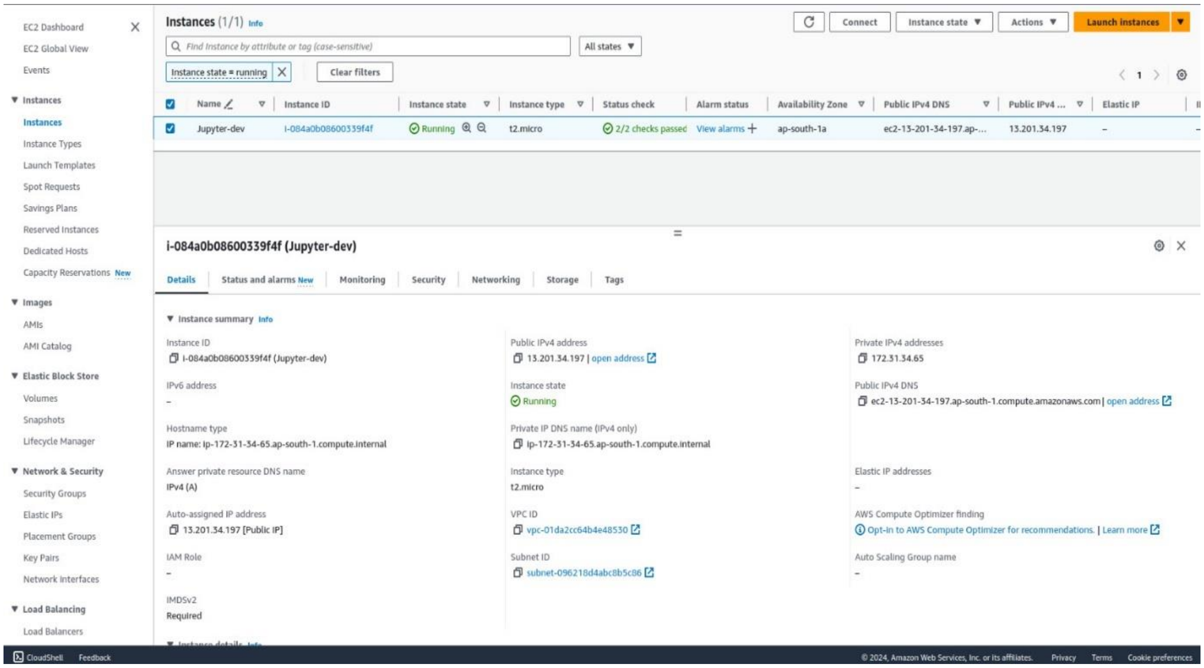

Fig 17

Cloud Interface

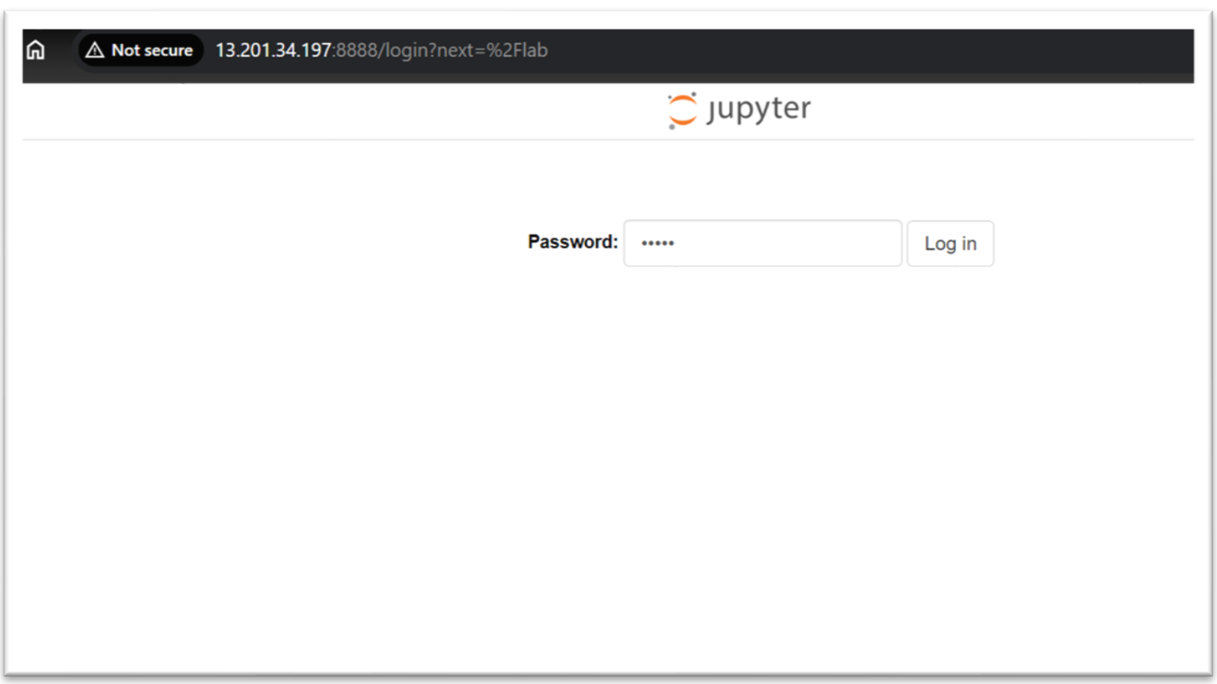

Fig 18

Login Page

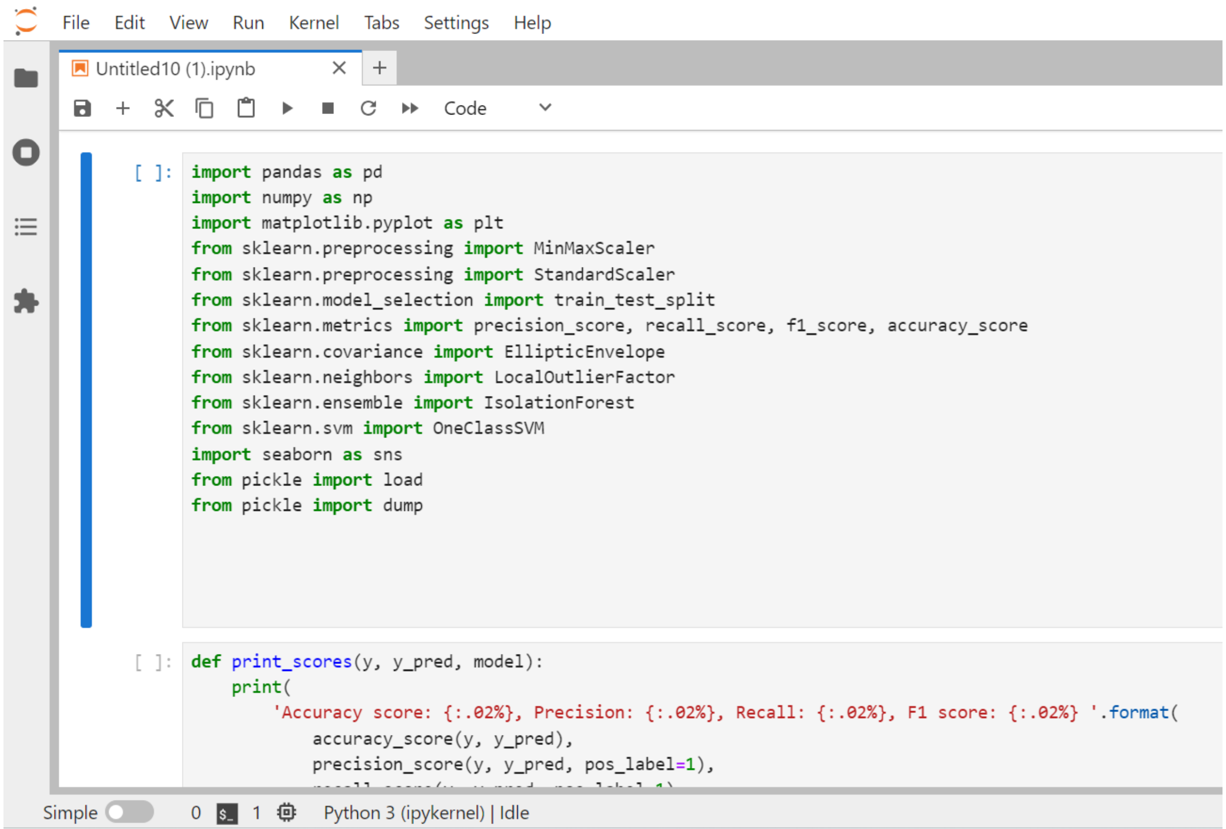

Fig 19

Jupyter File

CHAPTER 6: CONCLUSIONS AND FUTURE SCOPE

6.1 Conclusion

The quest of operational excellence in the quickly changing world of industrial operations is inextricably linked to making use of cutting-edge technology. This project presents a novel initiative: the application of cloud-based predictive maintenance on industrial equipment. It recognizes the urgent need for a paradigm shift in maintenance practices. The objective of this strategic approach is to tackle the ongoing obstacles caused by equipment failure, which has a substantial influence on the productivity, operational effectiveness, and overall financial gain of industrial domains.

A growing number of people believe that traditional maintenance strategies, which involve reactive and schedule-based interventions, are insufficient to handle the complexity of today's industrial environment. Industry 4.0's arrival emphasizes how crucial it is to adopt cutting-edge technology in order to rethink operational procedures. By concentrating on predictive maintenance, which is the core of the transformation, the project plays a crucial role in this transformative endeavor. The project aims to transform industry maintenance and equipment management through the creative integration of machine learning, data analytics, and cloud computing.

Advantages

Innovative Technological Foundation: Our predictive maintenance initiative creates an innovative technological foundation by integrating cloud computing, data analytics, and machine learning. This accomplishment not only establishes a new standard in the industry, but it also sets the stage for a revolutionary method of maintaining industrial machinery. The combination of these cutting-edge technologies paves the way for a maintenance paradigm that is more proactive, effective, and data-driven.

Improvement of Operational Efficiency: Our project seeks to make a major contribution to the improvement of operational efficiency in industrial sectors by concentrating on predictive maintenance. When cloud-based predictive maintenance is implemented successfully, production schedules will be optimized, equipment downtime will be minimized, and overall profitability will increase. This accomplishment addresses a crucial need in the modern industrial landscape and represents a concrete and significant contribution to the operational excellence of industrial processes.

Considerations

User Adoption and Interface Improvement: By giving priority to user interface and experience enhancements, the blockchain-powered crowdfunding platform acknowledges the significance of improving user adoption and guarantees a smooth and captivating user experience.

Regulatory compliance and security audits: Understanding that, in the ever-changing world of blockchain technology and crowdsourcing, stringent security audits and compliance checks are essential to establishing and preserving user trust.

Exploration of Scalability Solutions: Taking into account the need for ongoing research into scalability solutions in order to guarantee the platform's capacity to manage expanding user demands and preserve competitiveness in the changing crowdfunding market.

Potential Improvements

Enhanced security measures include limiting access to certain functions to authorized users only by putting advanced access control and validation mechanisms in place. With this improvement, users and stakeholders should feel more confident in the platform's overall security posture.

Robust Error Handling: To guarantee safer and more predictable behavior, the smart contract should include revert conditions and strong error handling. This enhancement increases the overall dependability of the crowdsourcing platform driven by blockchain technology while reducing possible risks.

6.2 Future Scope

Predictive maintenance initiatives have a lot of room to grow in the future, offering ongoing innovation and operational optimization in the industrial sector. The scope covers a number of important areas, including community building, security updates, scalability solutions, and user interface improvements.

In order to encourage wider adoption, one of the main priorities going forward will be to enhance user interfaces and experiences. On the horizon are social integration features, mobile applications, and intuitive interfaces that are intended to improve user engagement and offer real-time insights into the health of the equipment. To increase user participation, proactive notifications and personalized dashboards are planned.

Upgrades related to security and compliance are crucial factors. Establishing and sustaining user trust will require strict compliance with changing regulatory frameworks and thorough audits of smart contracts. As the platform gains traction, strengthening defenses against vulnerabilities ensures the platform's integrity.

Future developments will prioritize scalability. It will be essential to investigate off-chain scaling options and interoperability with various blockchain networks in order to meet the expanding needs of industrial operations. This flexibility guarantees the platform's robustness and interoperability across diverse technological environments.

Strategic alliances and community-building initiatives will be essential to the platform's expansion. By forming relationships with thought leaders in the field, academic institutions, and technology companies, it will reach a wider audience and enable ongoing development by exchanging knowledge and resources.

In terms of future scope, one significant advancement is the incorporation of AI-driven analytics. By using artificial intelligence to extract predictive insights for campaign success, this enables industries to make more informed decisions and more precisely optimize maintenance strategies.

To encourage active participation, smart contract automation and more tokenization strategy research are planned. The automation of industrial processes is in line with this upcoming development, which will benefit both the platform and the industries.

To sum up, the predictive maintenance initiative's future focus will be on user-centric enhancements, improved security protocols, scalability strategies, and strategic alliances. This roadmap for the future seeks to empower industries, redefine maintenance standards, and establish an open and inclusive industrial environment. This project's continuous development is evidence of its flexibility and durability in influencing predictive maintenance's future in the ever-changing field of industrial operations.

REFERENCES

[1] M. A. Hoffmann and R. Lasch, "Tackling industrial downtimes with Artificial Intelligence in data-driven maintenance," ACM Comput. Surv., vol. 56, no. 4, pp. 1–33, 2024.

[2] M. Molęda, B. Małysiak-Mrozek, W. Ding, V. Sunderam, and D. Mrozek, "From corrective to predictive maintenance—A review of maintenance approaches for the power industry," Sensors (Basel), vol. 23, no. 13, p. 5970, 2023.

[3] M. Achouch et al., "On predictive maintenance in Industry 4.0: Overview, models, and challenges," Appl. Sci. (Basel), vol. 12, no. 16, p. 8081, 2022.

[4]N. Burmeister, R. D. Frederiksen, E. Høg, and P. Nielsen, "Exploration of production data for predictive maintenance of industrial equipment: A case study," *IEEE Access*, vol. 11, pp. 102025–102037, 2023.

[5]W. Tiddens, J. Braaksma, and T. Tinga, "Exploring predictive maintenance applications in industry," *J. Qual. Maint. Eng.*, vol. 28, no. 1, pp. 68–85, 2022.

[6] W. J. Lee, H. Wu, H. Yun, H. Kim, M. B. G. Jun, and J. W. Sutherland, "Predictive maintenance of machine tool systems using artificial intelligence techniques applied to machine condition data," Procedia CIRP, vol. 80, pp. 506–511, 2019.

[7] M. Pech, J. Vrchota, and J. Bednář, "Predictive maintenance and intelligent sensors in smart factory: Review," Sensors (Basel), vol. 21, no. 4, p. 1470, 2021.

[8] D.-G. Kim and J.-Y. Choi, "Optimization of design parameters in LSTM model for predictive maintenance," Appl. Sci. (Basel), vol. 11, no. 14, p. 6450, 2021.

[9] R. Fila, M. E. Khaili, and M. Mestari, “Cloud computing for industrial predictive maintenance based on prognostics and health management,” Procedia Comput. Sci., vol. 177, pp. 631–638, 2020.

[10] J. Wang, L. Zhang, L. Duan, and R. X. Gao, “A new paradigm of cloud-based predictive maintenance for intelligent manufacturing,” J. Intell. Manuf., vol. 28, no. 5, pp. 1125–1137, 2017.

[11] B. Schmidt and L. Wang, “Cloud-enhanced predictive maintenance,” Int. J. Adv. Manuf. Technol., vol. 99, no. 1–4, pp. 5–13, 2018.

[12]Darian Daji; Kedar Ghule; Sarthak Gagdani, “Cloud-Based Asset Monitoring and Predictive Maintenance in an Industrial IoT System” *IEEE Access*, vol. 11, pp. 102025–102037, 2020.

[13] D. Mourtzis, E. Vlachou, N. Milas, and N. Xanthopoulos, “A cloud-based approach for maintenance of machine tools and equipment based on shop-floor monitoring,” Procedia CIRP, vol. 41, pp. 655–660, 2015.

[14] M. Paolanti, L. Romeo, A. Felicetti, A. Mancini, E. Frontoni, and J. Loncarski, “Machine Learning approach for Predictive Maintenance in Industry 4.0,” in 2018 14th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA), 2018.

[15] S. Farahani, V. Khade, S. Basu, and S. Pilla, “A data-driven predictive maintenance framework for injection molding process,” J. Manuf. Process., vol. 80, pp. 887–897, 2022.

[16] S. Geng and X. Wang, “Predictive maintenance scheduling for multiple power equipment based on data-driven fault prediction,” Comput. Ind. Eng., vol. 164, no. 107898, p. 107898, 2022.

[17] K. Shukla, S. Nefti-Meziani, and S. Davis, “A heuristic approach on predictive maintenance techniques: Limitations and scope,” Adv. Mech. Eng., vol. 14, no. 6, p. 168781322211010, 2022.

[18] L. Xia, P. Zheng, X. Li, R. X. Gao, and L. Wang, “Toward cognitive predictive maintenance: A survey of graph-based approaches,” *J. Manuf. Syst.*, vol. 64, pp. 107–120, 2022.

[19]A. Latrach, “Application of deep learning for predictive maintenance of oilfield equipment,” *arXiv [stat.ML]*, 2023.

[20]M. Nacchia, F. Fruggiero, A. Lambiase, and K. Bruton, “A systematic mapping of the advancing use of machine learning techniques for predictive maintenance in the manufacturing sector,” *Appl. Sci. (Basel)*, vol. 11, no. 6, p. 2546, 2021.

[21]P. Kruczek *et al.*, “Predictive maintenance of mining machines using advanced data analysis system based on the cloud technology,” in *Proceedings of the 27th International Symposium on Mine Planning and Equipment Selection - MPES 2018*, Cham: Springer International Publishing, 2019, pp. 459–470.

[22]Y. You, C. Chen, F. Hu, Y. Liu, and Z. Ji, “Advances of digital twins for predictive maintenance,” *Procedia Comput. Sci.*, vol. 200, pp. 1471–1480, 2022.

[23]S. T. March and G. D. Scudder, “Predictive maintenance: strategic use of IT in manufacturing organizations,” *Inf. Syst. Front.*, vol. 21, no. 2, pp. 327–341, 2019.

[24]W. Luo, T. Hu, Y. Ye, C. Zhang, and Y. Wei, “A hybrid predictive maintenance approach for CNC machine tool driven by Digital Twin,” *Robot. Comput. Integr. Manuf.*, vol. 65, no. 101974, p. 101974, 2020.

[25]A. Buabeng, A. Simons, N. K. Frempong, and Y. Y. Ziggah, “Hybrid intelligent predictive maintenance model for multiclass fault classification,” *Soft Comput.*, 2023.