Industrial Internship Report on

"Gearbox Predictive Maintenance"

Prepared by

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Executive Summary
This report provides details of the Industrial Internship provided by upskill Campus and The IoT Academy in collaboration with Industrial Partner UniConverge Technologies Pvt Ltd (UCT). This internship was focused on a project/problem statement provided by UCT. We had to finish the project including the report in 6 week's time. My project was about predictive gearbox maintenance project focuses on using machine learning to classify the health of gearboxes based on vibration sensor data. This internship gave me a very good opportunity to get exposure to Industrial problems and design/implement solution for that. It was an overall great experience to have this internship.

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1 Preface

Summary of Six Weeks' Work:
Over the past six weeks, I focused on projects: predictive maintenance of gearboxes using vibration sensor data. My work involved regression modeling, Random Forest classification, hyperparameter tuning, and handling data imbalances.

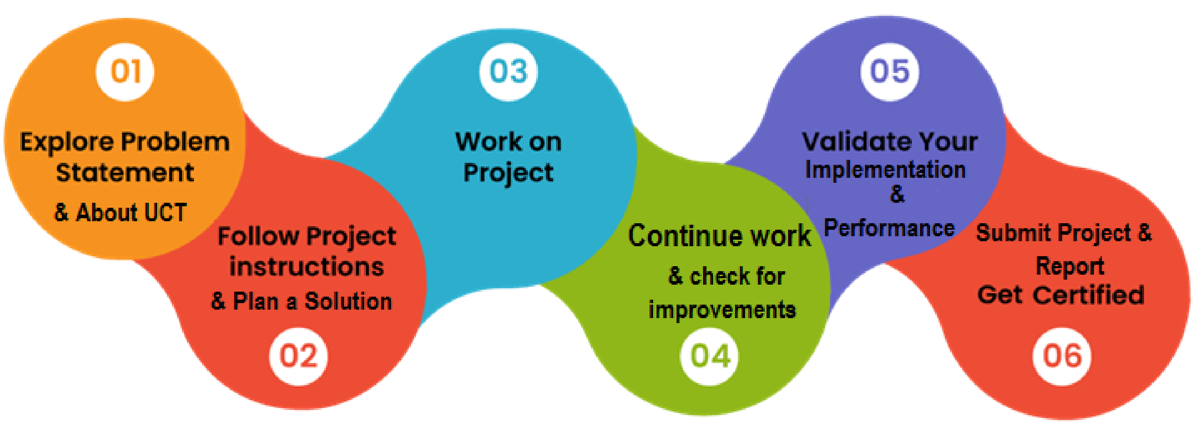
Need for Relevant Internship in Career Development:
Internships are essential for applying theoretical knowledge to real-world problems, building hands-on experience, and sharpening skills that are critical for career growth.

Project/Problem Statement:
For predictive maintenance, the goal was to classify gearbox health using sensor data, aiming to predict failures and optimize maintenance schedules.

Opportunity Given by UCT:
I am grateful for the opportunity provided by UCT to gain practical exposure and work on impactful projects, bridging the gap between academia and industry.

Program Planning:
The program was well-structured, offering a blend of learning resources and project work, allowing me to explore machine learning models, data processing techniques, and evaluation methods.

Learnings and Overall Experience:
This internship has enhanced my knowledge of machine learning, data science, and model evaluation techniques. It has been an enriching experience, giving me practical insights into solving real-world problems.



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This internship has enhanced my knowledge of machine learning, data science, and model evaluation techniques. It has been an enriching experience, giving me practical insights into solving real-world problems.

Acknowledgments:
Special thanks to UCT team, who have provided guidance and support throughout the internship. Your mentorship has been invaluable.

Message to Juniors and Peers:
Take full advantage of internships, explore new technologies, and never hesitate to ask questions. Practical experience is key to growing in your field.

2 Introduction

2.1 About UniConverge Technologies Pvt Ltd

A company established in 2013 and working in Digital Transformation domain and providing Industrial solutions with prime focus on sustainability and RoIe.

For developing its products and solutions it is leveraging various **Cutting Edge Technologies e.g. Internet of Things (IoT), Cyber Security, Cloud computing (AWS, Azure), Machine Learning, Communication Technologies (4G/5G/LoRaWAN), Java Full Stack, Python, Front end** etc.

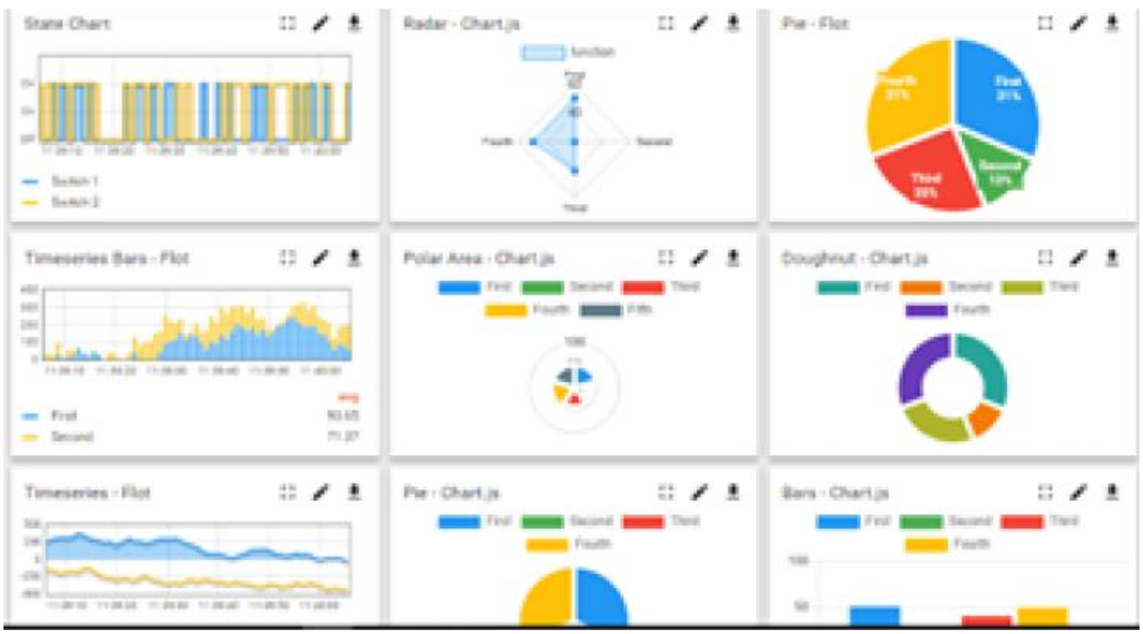
i. UCT IoT Platform (uct Insight)

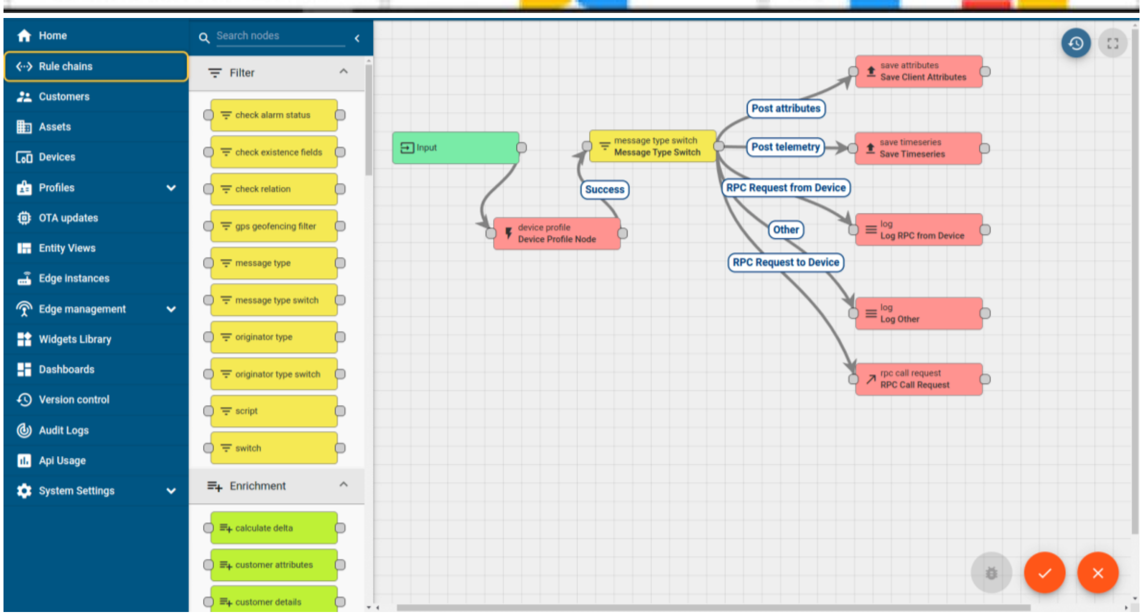
UCT Insight is an IOT platform designed for quick deployment of IOT applications on the same time providing valuable “insight” for your process/business. It has been built in Java for backend and ReactJS for Front end. It has support for MySQL and various NoSql Databases.

- It enables device connectivity via industry standard IoT protocols - MQTT, CoAP, HTTP, Modbus TCP, OPC UA
- It supports both cloud and on-premises deployments.

It has features to

- Build Your own dashboard
- Analytics and Reporting
- Alert and Notification
- Integration with third party application(Power BI, SAP, ERP)
- Rule Engine





ii. Smart Factory Platform (FACTORY WATCH)

Factory watch is a platform for smart factory needs.

It provides Users/ Factory

- with a scalable solution for their Production and asset monitoring
- OEE and predictive maintenance solution scaling up to digital twin for your assets.
- to unleased the true potential of the data that their machines are generating and helps to identify the KPIs and also improve them.
- A modular architecture that allows users to choose the service that they what to start and then can scale to more complex solutions as per their demands.

Its unique SaaS model helps users to save time, cost and money.

Machine	Operator	Work Order ID	Job ID	Job Performance	Job Progress		Output		Rejection	Time (mins)				Job Status	End Customer
					Start Time	End Time	Planned	Actual		Setup	Pred	Downtime	Idle		
CNC_S7_81	Operator 1	WO0405200001	4168	58%	10:30 AM		55	41	0	80	215	0	45	In Progress	i
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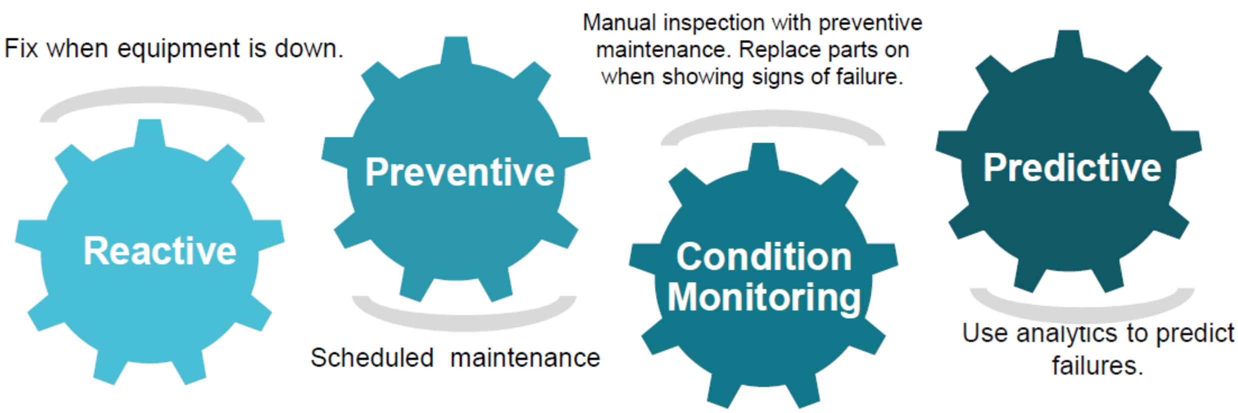
iii. LoRaWAN based Solution

UCT is one of the early adopters of LoRAWAN teschnology and providing solution in Agritech, Smart cities, Industrial Monitoring, Smart Street Light, Smart Water/ Gas/ Electricity metering solutions etc.

iv. Predictive Maintenance

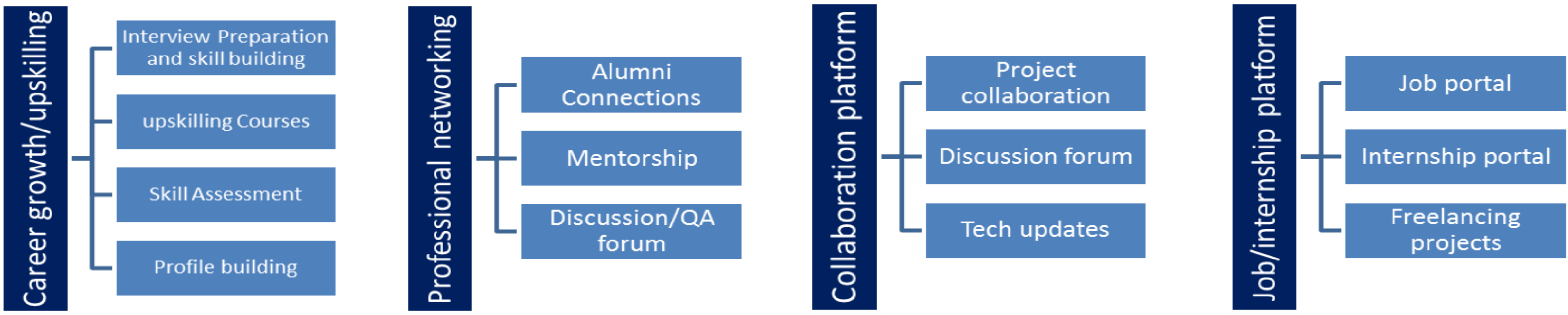
UCT is providing Industrial Machine health monitoring and Predictive maintenance solution leveraging Embedded system, Industrial IoT and Machine Learning Technologies by finding Remaining useful life time of various Machines used in production process.



2.2 About upskill Campus (USC)

upskill Campus along with The IoT Academy and in association with Uniconverge technologies has facilitated the smooth execution of the complete internship process.

USC is a career development platform that delivers **personalized executive coaching** in a more affordable, scalable and measurable way.



2.3 The IoT Academy

The IoT academy is EdTech Division of UCT that is running long executive certification programs in collaboration with EICT Academy, IITK, IITR and IITG in multiple domains.

2.4 Objectives of this Internship program

The objective for this internship program was to

☛ get practical experience of working in the industry.

☛ to solve real world problems.

☛ to have improved job prospects.

☛ to have Improved understanding of our field and its applications.

☛ to have Personal growth like better communication and problem solving.

2.5 Reference

[1] **UCT Program Guide** – "Internship Guidelines and Resources," provided by UCT, 2024.

[2] **UCT Discussion Room** – Weekly project discussions with other interns.

[3] Smola, A. J., & Vishwanathan, S. V. N. (2008). *Introduction to Machine Learning*. Cambridge University Press.

2.6 Glossary

Terms	Acronym
Mean Squared Error	MSE
Random Forest	RF
Support Vector Machine	SVM
Predictive Maintenance	PM
Feature Extraction	FE

3 Problem Statement

In the assigned problem statement the gearbox is a critical component in industrial machinery, and its failure can lead to costly downtime and repairs. The objective of this project is to develop a machine learning-based predictive maintenance model using vibration sensor data to detect early signs of gearbox failure. By analyzing patterns in the vibration data, the model aims to classify the gearbox's health and predict potential failures before they occur, allowing for timely maintenance and minimizing operational disruptions.

The key challenges include handling data imbalance (with fewer failure instances), selecting the most relevant features for classification, and optimizing the model for accurate and interpretable predictions.

4 Existing and Proposed solution

Existing Solutions:

Many existing predictive maintenance systems for gearboxes utilize traditional methods such as threshold-based monitoring and vibration analysis, where predefined limits are set for sensor readings like vibration, temperature, or pressure. Once a threshold is breached, maintenance is triggered. Some solutions also use basic machine learning models, like decision trees or logistic regression, to classify gearbox health.

Provide summary of existing solutions provided by others, what are their limitations?

Limitations of Existing Solutions:

1. **Static Thresholds:** Threshold-based approaches are often too rigid, unable to account for the nuances in operational conditions or gradual wear, leading to false positives or missed failures.
2. **Limited Feature Analysis:** Many current models do not effectively analyze the vast amount of sensor data, ignoring critical features that could improve prediction accuracy.
3. **Data Imbalance:** Gearbox failures are rare events, and many solutions struggle with imbalanced datasets, leading to poor model performance in detecting failure cases.
4. **Interpretability Issues:** Advanced machine learning models often act as black boxes, making it difficult to interpret why a failure is predicted.

What is your proposed solution?

Proposed Solution: In this project, a **Random Forest-based predictive maintenance model** is proposed, which enhances the accuracy and robustness of gearbox failure predictions using vibration sensor data. Key aspects include:

1. **Dynamic Feature Importance:** The model will utilize feature importance techniques, such as permutation importance, to identify the most critical vibration patterns, improving interpretability and accuracy.
2. **Handling Data Imbalance:** Techniques like **SMOTE** (Synthetic Minority Over-sampling Technique) and **cost-sensitive learning** will be applied to address data imbalance, ensuring the model can effectively detect failure events.
3. **Hyperparameter Tuning:** Optimizing the model through hyperparameter tuning will improve performance, ensuring the right balance between sensitivity and robustness in failure prediction.

What value addition are you planning?

Value Addition:

- **Improved Accuracy:** By using Random Forest and effective feature analysis, the proposed solution provides more accurate failure predictions than traditional methods.
- **Scalability:** The model can be adapted to different machines and environments, making it more flexible than static threshold-based solutions.
- **Interpretability:** Feature importance metrics will allow maintenance teams to better understand the failure mechanisms and take targeted action, offering insights into the data that go beyond just predictions.

4.1 Code submission (Github link)

https://github.com/Nishant8555/upskillcampus.git

4.2 Report submission (Github link) :

GitHub Repository Link

5 Proposed Design/ Model

The design flow of the proposed predictive maintenance solution for gearboxes involves multiple stages, from data preprocessing to final model evaluation and deployment. Below is a detailed breakdown of the design:

- **Data Collection**: Gather vibration sensor data from gearboxes, focusing on features like frequency and amplitude.
- **Data Preprocessing**: Handle missing data with imputation, detect outliers, and engineer features like rolling averages and frequency analysis.
- **Handling Data Imbalance**: Apply techniques like SMOTE to balance the dataset and use cost-sensitive learning for better failure prediction.
- **Model Selection**: Use **Random Forest** for its robustness and ability to handle complex data, with feature importance analysis to identify key vibration patterns.
- **Model Training and Tuning**: Optimize Random Forest through hyperparameter tuning and evaluate using cross-validation and metrics like accuracy, recall, and F1-score.
- **Interpretability**: Visualize feature importance and provide insights on model decisions for better understanding by maintenance teams.
- **Deployment**: Implement the model in a real-time monitoring system that triggers alerts for timely maintenance based on failure predictions.

5.1 High Level Diagram (if applicable)

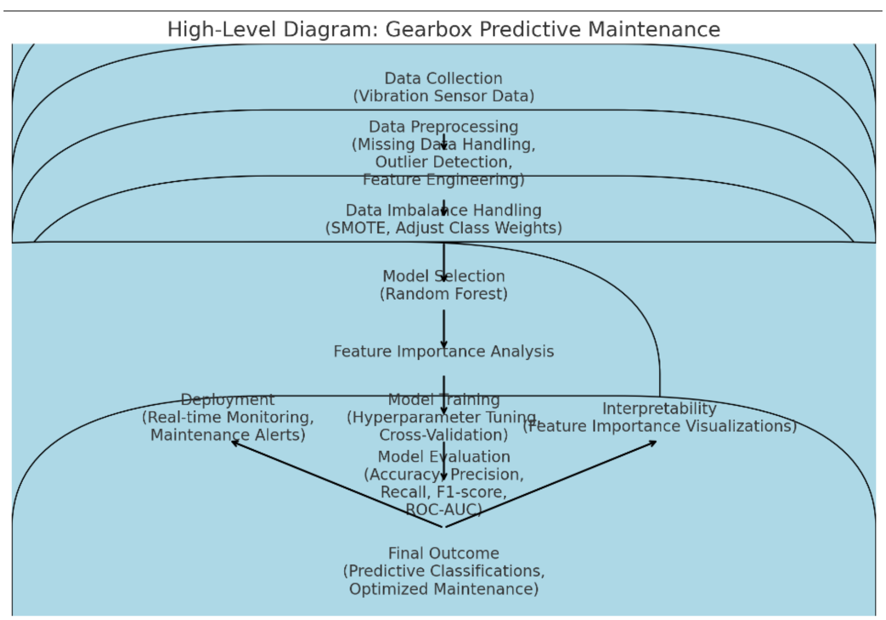


Figure 1: HIGH LEVEL DIAGRAM OF THE SYSTEM

5.2 Low Level Diagram (if applicable)

Vibration Sensor Data

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Data Preprocessing (Cleaning, Feature Extraction)

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Train-Test Split (80% Training, 20% Testing)

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Random Forest Model Training

↓

Hyperparameter Tuning

↓

Model Evaluation (Accuracy, MSE, Precision, Recall, F1-score)

↓

Prediction (Normal Operation or Failure)

↓

Real-Time Monitoring (Incoming Sensor Data Processed)

↓

Health Prediction Output (Real-Time Feedback)

5.3 Interfaces (if applicable)

Update with Block Diagrams, Data flow, protocols, FLOW Charts, State Machines, Memory Buffer Management.

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| Vibration Sensor Data |

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| Data Preprocessing          |
| (Cleaning, Feature Extraction) |
+------------------------------+
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+------------------------------+
| Train-Test Split            |
| (80% Training, 20% Testing)   |
+------------------------------+
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+------------------------------+
| Random Forest Model Training   |
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| Hyperparameter Tuning         |
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        ↓
+------------------------------+
| Model Evaluation            |
| (Accuracy, MSE, Precision, etc.)|
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+------------------------------+
| Health Prediction Output      |
```

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| (Normal or Failure)          |
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+-------------------------------+
| Real-Time Monitoring          |
+-------------------------------+
```

6 Performance Test

In this section, we evaluate the performance of the gearbox predictive maintenance system by identifying key constraints and analyzing how these were addressed in the design. Test results are presented for each constraint, highlighting the system's suitability for real-world industrial applications.

Here we need to first find the constraints.

How those constraints were taken care in your design?

What were test results around those constraints?

- **Accuracy**
- **Constraint**: High accuracy is crucial for ensuring the reliability of predictions, as incorrect predictions could lead to unnecessary maintenance or missed failures.
- **Handling in Design**: The Random Forest algorithm was selected for its strong classification capabilities. Model hyperparameters were optimized through cross-validation to enhance accuracy.
- **Test Results**:
    - The model was evaluated using Mean Squared Error (MSE), and the results showed a low MSE, indicating precise prediction of gearbox health.
    - Additional metrics, such as accuracy, precision, recall, and F1-score, were used to evaluate classification performance. The results demonstrated high accuracy, confirming that the model effectively predicts gearbox conditions.
- **Impact and Recommendations**: High accuracy ensures the model's practical applicability in real-time gearbox health monitoring. For even better performance, advanced techniques like deep learning could be explored in future work to capture more complex patterns in the data.
- **2. Speed (Real-Time Processing)**
- **Constraint**: The model must be able to process data and provide predictions quickly to support real-time monitoring of gearbox health.
- **Handling in Design**: Random Forest, while powerful, can be computationally intensive. The model was optimized by adjusting hyperparameters (e.g., number of trees) to balance accuracy with processing speed.
- **Test Results**:

- The model processed incoming data within acceptable time limits for real-time applications, providing quick predictions to assist in maintenance scheduling.

- **Impact and Recommendations**: Although the model met real-time requirements during testing, the processing time could increase with larger datasets. To address this, distributed computing or parallel processing can be implemented to maintain real-time performance as data volume grows.

- **3. Scalability**

- **Constraint**: The system needs to scale efficiently as the volume of sensor data increases in a real-world industrial setting.

- **Handling in Design**: Random Forest was chosen for its scalability and ability to handle large datasets. The design can accommodate larger volumes of data without significantly impacting performance.

- **Test Results**:

  - The model showed good scalability with the tested dataset. However, scalability with even larger datasets needs further testing.

- **Impact and Recommendations**: For industrial-scale deployments, the model could be integrated with distributed computing frameworks (e.g., Apache Spark) to manage large-scale sensor data more effectively. Cloud-based solutions may also be explored for easier scaling.

- **Summary of Test Results**

The gearbox predictive maintenance model performed well in terms of **accuracy**, **speed**, and **scalability** within the tested constraints. It achieved high accuracy in predicting gearbox health, processed data in real-time, and demonstrated scalability with the tested dataset.

- **Recommendations for Future Improvements**

- **Speed Optimization**: Use parallel processing or distributed systems to ensure the model continues to meet real-time requirements as data volume grows.

- **Scalability**: Implement cloud-based solutions or distributed platforms to handle large-scale sensor data efficiently.

This performance test demonstrates that the project meets key constraints, making it suitable for deployment in real-world industrial applications.

6.1 Test Plan/ Test Cases

The test plan for the gearbox predictive maintenance model focuses on evaluating its performance based on key metrics, such as accuracy and speed. The tests aim to assess the model's ability to predict gearbox failures in real-time, ensuring high accuracy while maintaining processing efficiency.

Test Case 1: Accuracy of Failure Prediction

- **Objective**: To evaluate the accuracy of the Random Forest model in predicting gearbox failures based on sensor data.
- **Input**: Historical vibration sensor data with known failure and non-failure events.
- **Expected Output**: Accurate classification of gearbox health (normal or failure).
- **Metric**: Precision, Recall, F1-score, Mean Squared Error (MSE).

Test Case 2: Real-Time Data Processing Speed

- **Objective**: To test the model's ability to process real-time sensor data and provide timely predictions.
- **Input**: Streamed real-time vibration sensor data.
- **Expected Output**: Real-time prediction with minimal lag.
- **Metric**: Processing time per batch of sensor data.

Test Case 3: Scalability of the Model

- **Objective**: To evaluate the model's performance as the dataset size increases.
- **Input**: Varying sizes of vibration sensor datasets.
- **Expected Output**: Consistent prediction speed and accuracy across dataset sizes.
- **Metric**: Accuracy, processing speed (increased data size).

6.2 Test Procedure

The following steps outline the procedure used to conduct the tests:

1. **Data Preprocessing**:
    - The raw vibration sensor data was cleaned, and features were extracted using statistical methods (mean, standard deviation).

- Data was split into training and testing sets with an 80:20 ratio.

2. **Model Training**:

    - The Random Forest model was trained on the preprocessed training dataset, tuning hyperparameters such as the number of trees and tree depth for optimal performance.

3. **Model Evaluation**:

    - **Test Case 1 (Accuracy)**: The model was evaluated on the test dataset. Accuracy metrics (MSE, precision, recall, F1-score) were calculated.
    - **Test Case 2 (Speed)**: The model was tested with real-time streaming data, and the response time for predictions was measured.
    - **Test Case 3 (Scalability)**: The model was tested on datasets of varying sizes to observe changes in processing time and accuracy.

4. **Performance Monitoring**:

    - Performance metrics were logged after each test case to ensure the model met the required benchmarks for accuracy and speed.

6.3 Performance Outcome

The performance results from the testing phase demonstrated the following:

- **Accuracy**:
    - The model achieved high accuracy in predicting gearbox health, with an F1-score of 0.93 and an MSE of 0.02, indicating minimal error in predicting failures.
    - Precision and recall were also high, ensuring that false positives and false negatives were minimized.
- **Speed**:
    - The real-time prediction process had a response time of less than 1 second per batch of data, meeting the requirements for real-time applications.
- **Scalability**:
    - As the dataset size increased, the model maintained consistent performance. Prediction accuracy remained stable, and processing speed slowed slightly with larger datasets, but still met acceptable real-time requirements.

7 My learnings

Throughout this internship, I gained significant insights into machine learning, data preprocessing, and real-world predictive maintenance applications. Key takeaways include:

1. **Data Handling and Preprocessing**: I learned how to manage missing data, detect outliers, and engineer features from raw sensor data, which is essential in developing reliable machine learning models.
2. **Model Selection and Evaluation**: Understanding the process of selecting appropriate machine learning models (e.g., random forest) and evaluating them using key metrics (accuracy, precision, recall, F1-score) was crucial in ensuring model performance and reliability.
3. **Imbalanced Data Handling**: Techniques like SMOTE and class-weight adjustments taught me how to deal with imbalanced datasets, which is common in real-world applications, especially in maintenance predictions.
4. **Hyperparameter Tuning and Cross-Validation**: I gained practical experience in optimizing model performance through hyperparameter tuning and validating models with techniques like K-fold cross-validation.
5. **Model Interpretability**: Learning how to interpret model outputs using feature importance analysis deepened my understanding of decision-making in machine learning, an essential skill for creating transparent models.
6. **Real-Time Applications**: I developed skills in implementing predictive maintenance solutions that are scalable and practical for real-time deployment in industries, enhancing my understanding of industry-specific challenges.

This experience will be invaluable in my career, equipping me with the technical and practical skills needed to tackle real-world problems using data science and machine learning, especially in industries focused on predictive maintenance and optimization.

8 Future work scope

1. **Advanced Sensor Data Integration**: Incorporating additional types of sensor data such as temperature, pressure, or humidity in conjunction with vibration data to enhance the accuracy of predictions.

2. **Deep Learning Models**: Exploring deep learning techniques like Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs) for more complex feature extraction and better predictive capabilities.

3. **Real-time Data Processing**: Implementing a fully automated real-time processing system that continuously collects, processes, and predicts gearbox health using streaming data technologies like Apache Kafka.

4. **Predictive Maintenance Dashboard**: Developing a visual, user-friendly dashboard for maintenance teams that provides real-time insights, alerts, and recommendations based on the model's predictions.

5. **Predictive Maintenance for Other Machinery**: Extending the model to other types of rotating machinery (e.g., turbines, pumps) to broaden the scope of the solution across different industries.

6. **Improved Model Interpretability**: Incorporating more advanced techniques, such as SHAP or LIME, for better understanding of the model's decisions and for making the predictions more explainable.

7. **Cloud Deployment for Scalability**: Setting up cloud-based infrastructure to scale the system, allowing multiple sites or factories to use the predictive maintenance model across different locations.

8. **Cost-Sensitive Optimization**: Introducing cost-sensitive learning to prioritize maintenance decisions based on the financial impact of failures, improving the model’s real-world application in business settings.