Industrial Internship Report

“Predict Life Time of a Bearing in Manufacturing Industry”

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Date of Submission: 28-06-2025

Executive Summary

This report documents my 4-week industrial internship, facilitated by upskill Campus and The IoT Academy in collaboration with UniConverge Technologies Pvt Ltd (UCT). The focus was on predicting the remaining useful life (RUL) of bearings in manufacturing machinery using vibration signal data and machine learning.

The project aimed to address a critical industrial challenge: reducing unplanned downtime and maintenance costs through predictive maintenance. By analyzing real-world vibration datasets, extracting meaningful features, and developing regression models, I worked towards a data-driven solution for RUL prediction. This internship provided invaluable exposure to real industry problems, advanced data science techniques, and the practical implementation of predictive maintenance solutions.

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1. Preface

This document summarizes my 6-week internship project on predicting bearing lifetime in manufacturing industries. The internship bridged the gap between academic learning and industry expectations, providing hands-on experience with real sensor data, signal processing, feature engineering, and machine learning model development.

Guided by mentors from USC and UCT, I learned to approach industrial problem statements, design solutions, and implement them practically using Python. I am grateful to my mentors and peers for their support and collaboration throughout this journey.

To juniors: Embrace such internships to gain practical knowledge, deepen your understanding of core concepts, and never hesitate to ask questions or try new approaches.

2. Introduction

2.1 About UniConverge Technologies Pvt Ltd

UniConverge Technologies Pvt Ltd (UCT), established in 2013, specializes in Digital Transformation with a focus on sustainability and Return on Investment (RoI). UCT develops products and solutions using:

- Internet of Things (IoT)
- Cyber Security
- Cloud Computing (AWS, Azure)
- Machine Learning
- Communication Technologies (4G/5G/LoRaWAN)
- Java Full Stack, Python, Front-end technologies

UCT’s platforms, such as UCT Insight and Smart Factory Platform, are designed for industrial monitoring, predictive maintenance, and analytics. UCT is also a pioneer in LoRaWAN technology for Agritech, Smart Cities, and Industrial Monitoring.

2.2 About upskill Campus (USC)

upskill Campus, in partnership with The IoT Academy and UCT, provided this internship opportunity. USC is a career development platform offering personalized coaching, internships, projects, industry interactions, and career guidance, all designed to upskill learners with industry-aligned projects.

2.3 Objective

The objectives of this internship were to:

- Gain practical industry experience
- Solve a real-world predictive maintenance problem
- Enhance job prospects
- Deepen understanding of IoT, machine learning, and their industrial applications
- Develop skills in communication, problem-solving, and teamwork

2.4 Reference

1. UCT official website
2. upskill Campus (https://www.upskillcampus.com)
3. Relevant academic papers on predictive maintenance

2.5 Glossary

Term	Meaning
RUL	Remaining Useful Life
IoT	Internet of Things
Vibration Signal	Sensor data capturing mechanical vibrations
Predictive Maintenance	Maintenance strategy predicting failures in advance

3. Problem Statement

"Predict life time of a bearing in manufacturing industry."

Bearings are critical to the operation of rotating machinery. Unexpected bearing failures can cause unplanned downtime, safety hazards, and increased costs. The goal was to predict the Remaining Useful Life (RUL) of bearings using vibration signal data from test-to-failure experiments, enabling predictive maintenance and proactive scheduling.

4. Existing and Proposed Solution

Existing Solutions

- **Reactive Maintenance:** Repairs after failure; leads to unexpected downtime.
- **Time-Based Maintenance:** Fixed schedules; may result in unnecessary replacements.
- **Condition-Based Monitoring:** Uses threshold alarms but does not predict failure time.

- **Signal Processing:** Used for monitoring, but often lacks robust predictive models.

Limitations

- Unexpected downtime and high costs with reactive approaches.
- Inefficiency and potential waste with time-based schedules.
- Lack of actionable RUL estimation in threshold-based monitoring.

Proposed Solution

- Develop a data-driven predictive maintenance model to estimate RUL using vibration signal data.
- Extract time and frequency-domain features from vibration signals.
- Train regression models (e.g., Random Forest, XGBoost, LSTM) for RUL prediction.

Value Addition:

- Enables planned, cost-effective maintenance.
- Increases machinery reliability and safety.
- Utilizes real sensor data for accurate predictions.

5. Proposed Design/Model

The solution comprises the following stages:

1. **Data Ingestion:**
   Load thousands of vibration signal files (e.g., IMS Rexnord Bearing dataset).
2. **Preprocessing:**
   Clean, normalize, and segment the data as needed.
3. **Feature Engineering:**
   Extract statistical (mean, variance, RMS, kurtosis) and frequency-domain features (FFT).
4. **Model Building:**
   Train regression models (Random Forest, XGBoost, LSTM) and validate using cross-validation.
5. **Evaluation:**
   Compare predicted RUL with actual failure cycles, analyze errors, and refine the model.

5.1 High Level Diagram

```text
Vibration Signals → Preprocessing → Feature Extraction → Regression Model → RUL Prediction
```

5.2 Low Level Diagram

- Raw data: .txt files with vibration snapshots

- Data parsing with Python
- Feature computation per file
- Model training and testing pipeline

5.3 Interfaces

- Python scripts for data loading and preprocessing
- Feature extraction modules
- Machine learning models (scikit-learn, TensorFlow)
- Visualization tools for predictions

6. Performance Test

6.1 Test Plan / Test Cases

- Test feature extraction on sample files
- Train models on part of the dataset, test on unseen data
- Validate prediction accuracy against known failure cycles

6.2 Test Procedure

- Batch load datasets to manage memory
- Apply standard scaling to features
- Use train-test splits and cross-validation for evaluation

6.3 Performance Outcome

- Models successfully captured degradation trends in early experiments
- Prediction accuracy depended on feature quality and dataset variability
- Identified the need for robust signal processing to reduce noise

7. My Learnings

- Gained practical understanding of predictive maintenance
- Developed advanced skills in signal processing and feature extraction for time-series data
- Learned to handle large, real-world datasets
- Built and validated regression models for RUL prediction
- Recognized the importance of domain knowledge in industrial applications
- Improved problem-solving, coding, and technical documentation abilities

8. Future Work Scope

- Expand feature set using wavelet transforms and advanced signal representations

- Experiment with deep learning architectures (CNN, LSTM) for raw signal processing
- Deploy the solution as a cloud-based predictive maintenance service
- Integrate with IoT sensors for real-time factory monitoring
- Extend methodology to other types of rotating equipment