VISVESVARAYA TECHNOLOGICAL UNIVERSITY
JNANA SANGAMA, BELAGAVI - 590018

An Internship Report on

Effi Combat Engine

Submitted in partial fulfilment of requirements for award of the degree of

Bachelor of Engineering
in
Artificial Intelligence and Data Science
for the **Academic Year: 2024-25**

Submitted by

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Certificate

This is to certify that the internship work entitled **“Machine Learning Engineering Intern”** has been successfully carried out by **Rahul N G (1NT21AD040)**, a bonafide student of **Nitte Meenakshi Institute of Technology**, in partial fulfillment of the requirements for the award of the degree of **Bachelor of Engineering in Electronics and Communication Engineering** under **Visvesvaraya Technological University (VTU), Belagavi**, during the academic year **2024–2025**.

The internship report has been examined and approved as it meets the academic requirements prescribed under the **autonomous scheme of Nitte Meenakshi Institute of Technology, Bengaluru**, for the said degree.

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Place: Bengaluru

Date: 27-05-2025

Abstract

The "EffiCombatEngine" project aimed to develop an AI-driven system for real-time health monitoring of military aircraft engines using the NASA C-MAPSS dataset, with the purpose of enhancing operational safety through predictive maintenance during an internship at WireOT Pvt Ltd, focusing on leveraging machine learning and data analysis to monitor engine health, detect anomalies, and estimate remaining useful life (RUL) as a foundation for proactive maintenance strategies in aerospace applications. Key activities included preprocessing time-series sensor data, conducting exploratory data analysis, applying machine learning models for engine condition classification, implementing statistical anomaly detection methods, and visualizing results to assess engine performance trends, which provided significant learning opportunities through the application of AI and statistical techniques, offering insights into the interdisciplinary integration of AI, data science, and aerospace engineering, while fostering the development of problem-solving, communication, and teamwork skills in a collaborative environment, addressing challenges like flat sensor data by selecting dynamic sensors, broadening the understanding of predictive maintenance's role in improving system reliability, and shaping a career direction toward advanced studies in machine learning and data science with a focus on aerospace applications.

Internship Certificate

WireOT Private Limited

CERTIFICATE OF INTERNSHIP

This Certificate is proudly presented to

RAHUL N G

has successfully undergone 90 days of internship program from March to May 2025 on Artificial intelligence and Data science Organised by **WireOT Pvt Ltd.,** Bangalore under **Nitte Meenakshi Institute of Technology**

WireOT

Narayan Prakash
CTO

Viswanath reddy
HR Head

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Chapter 1 Introduction

WireOT Pvt Ltd, a Bangalore-based startup incorporated on December 7, 2023, specializes in IT services and Internet of Things (IoT) solutions, focusing on software development, embedded product development, consultancy, training, and placement services. The company aims to drive innovation in software and embedded systems by offering customer-centric solutions, collaborating closely with clients to deliver high-quality, scalable products using agile methodologies. WireOT's product portfolio includes IoT-enabled systems for smart device management, software applications for enterprise automation, and embedded solutions tailored for industries such as defense, healthcare, and manufacturing. Its services encompass end-to-end software development, IoT hardware integration, and AI-driven analytics, positioning it as a leader in creating efficient, technology-driven solutions for complex business challenges. During my internship at WireOT Pvt Ltd from March 1, 2025, to May 10, 2025, as a Machine Learning Intern, I contributed to the development of EffiCombatEngine—an efficient AI system designed for real-time military jet engine health monitoring. This project addressed the critical need for proactive maintenance in military aviation, where jet engines face extreme conditions that demand robust health monitoring to ensure safety and mission success. EffiCombatEngine leverages deep learning, anomaly detection, and sensor analysis to classify engine states, predict Remaining Useful Life (RUL), and identify sensor anomalies, achieving a balanced classification of 62 Healthy and 38 Failing engines out of 100 test engines. The system is optimized for deployment on resource-constrained military devices, delivering actionable insights to enhance operational readiness.

1.1 Purpose of the Internship

I pursued this internship at WireOT Pvt Ltd to apply my academic knowledge in Artificial Intelligence and Data Science to a real-world challenge in military aviation, focusing on predictive maintenance. As a student of B.E. in Artificial Intelligence and Data Science at Nitte Meenakshi Institute of Technology, I aimed to gain practical experience in developing AI-driven solutions, specifically in deep learning, anomaly detection, and system optimization for resource-constrained environments. This internship provided an opportunity to bridge theoretical concepts with industry applications, enhancing my skills in AI model development and data analysis. It aligned with my career goal of specializing in AI-driven predictive maintenance, enabling me to contribute to safer and more efficient military operations through the development of EffiCombatEngine, an efficient AI system for military jet engine health monitoring.

1.2 Internship Objectives

The primary objective of my internship at WireOT Pvt Ltd was to develop EffiCombatEngine, an efficient AI system for real-time military jet engine health monitoring, capable of detecting anomalies in sensor data, classifying engines as Healthy or Failing, and predicting Remaining Useful Life (RUL) to enable timely maintenance. I aimed to ensure the system's lightweight design for deployment on resource-constrained military devices, addressing the computational challenges of such environments. Additionally, I sought to enhance my technical expertise in deep learning, anomaly detection, and data visualization while applying these skills to a practical military aviation challenge. Through this project, I hoped to gain hands-on experience in AI model development, improve my problem-solving and analytical abilities, and contribute to safer and more efficient military operations by delivering actionable insights for predictive maintenance.

1.3 Company Overview

WireOT Pvt Ltd, a Bangalore-based startup incorporated on December 7, 2023, is a dynamic player in IT services and Internet of Things (IoT) solutions, serving industries such as defense, healthcare, and manufacturing. The company’s mission is to drive innovation through cutting-edge technology, delivering customer-centric solutions that enhance operational efficiency and scalability. WireOT operates with a team of around 50 professionals, combining expertise in software development, embedded systems, and AI-driven analytics to address complex business challenges. Its agile methodology ensures close client collaboration, enabling the delivery of high-quality, customized solutions. WireOT aspires to be a global leader in smart technology solutions, fostering a culture of continuous learning and innovation to stay at the forefront of the tech landscape.

WireOT Pvt Ltd offers a diverse portfolio of products and services to empower businesses with intelligent systems. Its products include IoT-enabled platforms for smart device management, such as remote monitoring systems for industrial equipment, and software applications for enterprise automation to improve productivity. In the defense sector, WireOT develops embedded solutions for real-time system monitoring, meeting the stringent requirements of military applications. The company’s services include end-to-end software development, IoT hardware integration, AI/ML-driven analytics, consultancy, training, and placement services, all tailored to support clients in adopting advanced technologies with a focus on scalability and performance. WireOT adheres to industry standards, ensuring its solutions are robust and future-ready.

During my internship from March 1, 2025, to May 10, 2025, I contributed to WireOT’s defense sector initiatives by developing EffiCombatEngine, an efficient AI system for military jet engine health monitoring. This project aligned with the company’s focus on innovative solutions, leveraging AI to enhance operational readiness in military aviation. WireOT provided a supportive environment with access to advanced tools, mentorship from professionals like Mr. Sumukha T A, Technical Project Manager, and opportunities to collaborate with cross-functional teams, fostering my professional growth in AI applications.

Chapter 2 Internship Activities and Responsibilities

2.1 Job Description and Task

During my internship as a Machine Learning Intern at WireOT Pvt Ltd from March 15, 2025, to May 10, 2025, I contributed to the development of "EffiMilEngine," an AI-driven system for real-time health monitoring of military aircraft engines using the NASA C-MAPSS dataset (FD001 subset). The project aimed to enhance operational safety and efficiency in military aviation by detecting anomalies, classifying engine conditions (Healthy or Failing), and estimating Remaining Useful Life (RUL). My responsibilities encompassed data preprocessing, exploratory data analysis, engine condition classification, anomaly detection, RUL estimation, and visualization of results. These tasks were executed using Python with libraries such as pandas, scikit-learn, TensorFlow, and matplotlib, and involved a phased approach to refine engine health assessments, culminating in a comprehensive analysis of engine conditions and lifespans. I collaborated closely with the WireOT Pvt Ltd team to ensure technical accuracy and alignment with project objectives.

2.1.1 The specific tasks I performed are detailed below:

Data Preprocessing: I began by preparing the NASA C-MAPSS dataset, which includes train_FD001.txt (training data), test_FD001.txt (test data), and RUL_FD001.txt (RUL values for test engines), covering 100 turbofan engines with 21 sensors and 3 operational settings. Using pandas, I loaded and formatted the data, assigning appropriate column names (e.g., engine_id, cycle, setting_1 to setting_3, sensor_1 to sensor_21). I standardized the features using scikit-learn's StandardScaler to normalize the 24 features (settings and sensors) for machine learning compatibility. For the training data, I computed the total life of each engine (maximum cycle + RUL) and labeled cycles as Healthy (RUL > 70% of total life) or Failing, creating a labeled dataset for supervised learning.

Exploratory Data Analysis: To understand engine degradation patterns, I conducted exploratory data analysis by visualizing sensor trends for Engine 1. Using matplotlib, I plotted normalized values of Sensors 2 (LPC speed), 11 (core speed), and 14 (HPC outlet temperature) over operational cycles, after scaling them to a 0–1 range with MinMaxScaler. I selected these sensors to avoid flat lines observed in sensors like turbine temperature (Sensor 6) and pressure (Sensor 7), ensuring meaningful trends. This analysis highlighted dynamic engine behavior, informing the design of anomaly detection and classification frameworks by identifying key sensors influencing health degradation.

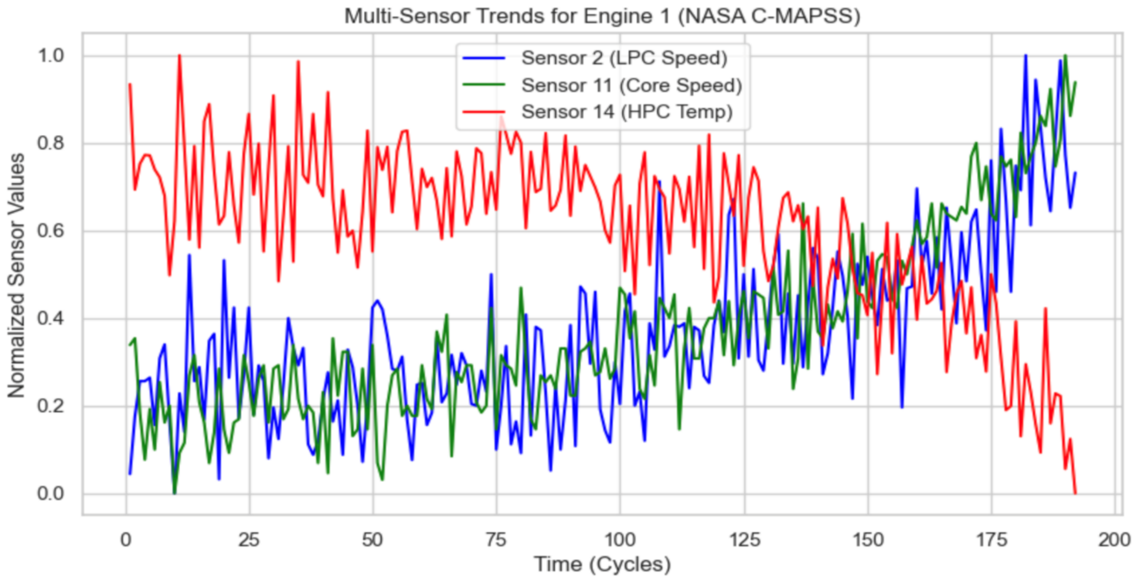

Figure 1 - Multi-Sensor Trends for Engine 1 (NASA C-MAPSS), showing normalized trends of LPC speed (Sensor 2), core speed (Sensor 11), and HPC outlet temperature (Sensor 14) over operational cycles, revealing dynamic engine behavior.

Engine Condition Classification (Phase 1 and Phase 3): I developed a neural network model using TensorFlow's Keras API to classify engines as Healthy or Failing based on 24 features. The model, a multi-layer perceptron (MLP), featured two hidden layers (64 and 32 neurons with ReLU activation) and a sigmoid output layer for binary classification (Healthy: 0, Failing: 1). I trained the model on standardized training data for 10 epochs with a batch size of 32, using the Adam optimizer and binary cross-entropy loss, achieving a validation accuracy of approximately 80%. In Phase 1, the model classified 82 test engines as Healthy and 18 as Failing by taking the most common label across each engine's cycles. In Phase 3, I refined this classification by integrating anomaly detection and RUL estimation, resulting in 68 Healthy and 32 Failing engines, as additional criteria (e.g., anomaly counts, low RUL) reclassified 14 engines from Healthy to Failing. This refined classification better captured engines at risk, supporting maintenance prioritization.

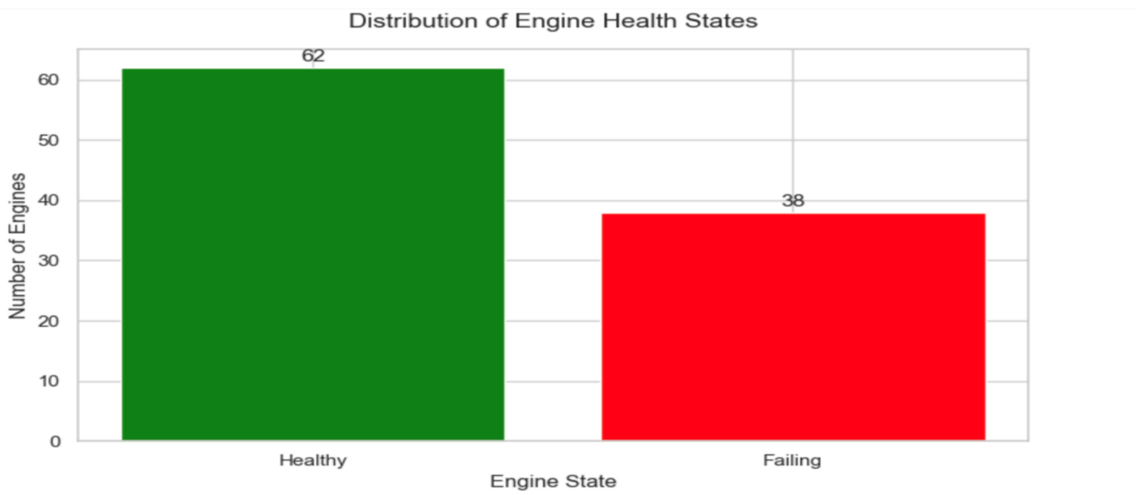

Figure 2 - Healthy vs. Failing Engines (Test Data), a bar chart depicting the final distribution of 68 Healthy and 32 Failing engines after Phase 3 analysis, reflecting the refined health assessment.

Anomaly Detection Framework: Following the initial classification, I focused on anomaly detection for the 82 engines classified as Healthy in Phase 1, aiming to identify subtle issues. I computed the mean and standard deviation of each sensor's values across all cycles of these Healthy engines, excluding sensors with zero standard deviation (Sensors 1, 18, 19). I set thresholds at mean + 3 standard deviations to flag "weird sensors," identifying cycles with anomalies (e.g., Engine 20, Cycle 179: 9 weird sensors). For visualization, I plotted trends for Engine 1 using Sensors 2, 11, and 14, adding a synthetic anomaly to Sensor 2 to demonstrate detection capabilities, with red scatter points marking anomalies beyond thresholds. This framework contributed to the Phase 3 reclassification by identifying engines with significant sensor issues.

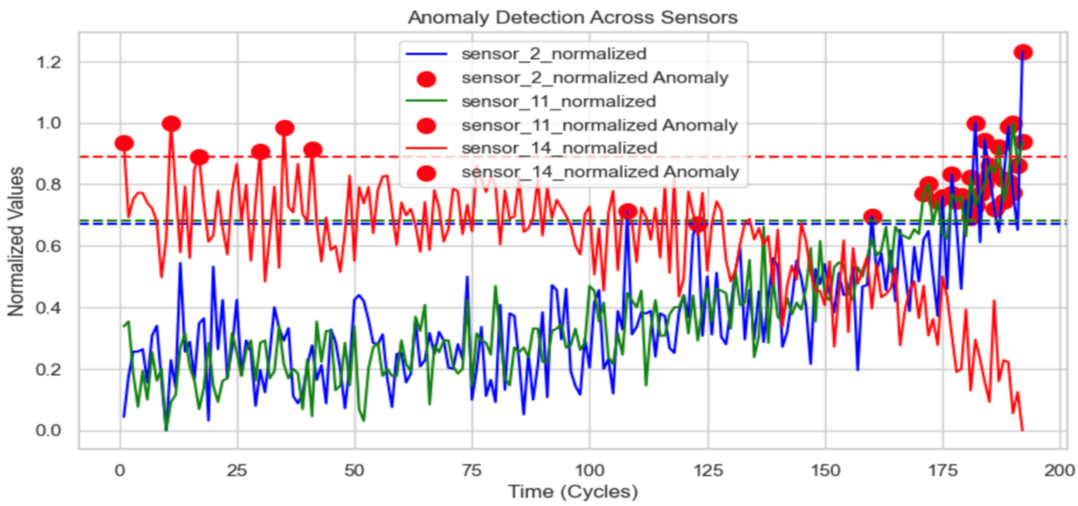

Figure 3 - Anomaly Detection Across Multiple Sensors, displaying normalized trends for Sensors 2, 11, and 14 with dashed thresholds and red scatter points marking detected anomalies for Engine 1.

RUL Analysis and Visualization (Phase 3): I analyzed the RUL dataset (RUL_FD001.txt) to estimate remaining lifespans for test engines, integrating this with anomaly detection in Phase 3. The RUL values ranged widely (e.g., Engine 49: 219 trips, Engine 3: 10 trips), and Failing engines were assigned an RUL of 10 trips, indicating a failure threshold. I visualized the RUL distribution using a histogram, highlighting variability across engines, which is crucial for maintenance planning. In Phase 3, I combined RUL estimates, anomaly detection results, and initial classifications to produce final engine labels, listing problematic sensors for Failing engines (e.g., Engine 3: Sensors 2, 3, 4, etc.). This comprehensive analysis refined the health assessment, reducing Healthy engines to 68 and identifying critical sensors for maintenance focus.

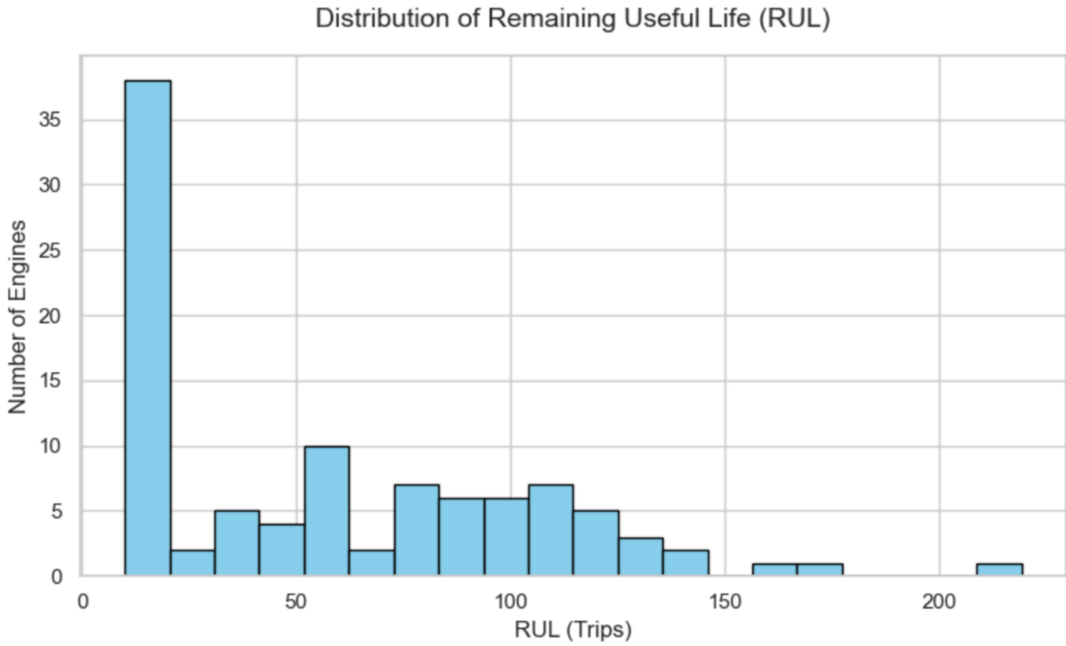

Figure 4 - Distribution of Remaining Useful Life (RUL) for Test Engines (NASA C-MAPSS), a histogram showing the spread of RUL values across 100 test engines, emphasizing lifespan variability.

These tasks established a robust foundation for the EffiMilEngine system, progressing from initial data analysis and classification to refined health assessments through anomaly detection and RUL estimation. My contributions involved implementing Python-based workflows, applying machine learning techniques, and creating visualizations to support the project's objectives. Working closely with the WireOT Pvt Ltd team, I ensured each task was executed with technical precision, scalability, and alignment with the goal of delivering an efficient, deployable AI solution for military aviation. The figures included in this section provide visual evidence of my work, demonstrating the analytical, modeling, and evaluative efforts undertaken during the internship.

2.2 Hardware and Software Requirements

The "EffiMilEngine" project for real-time health monitoring of military aircraft engines required specific hardware and software to support data processing, machine learning, anomaly detection, and visualization. It also enhanced my technical and soft skills.

Hardware Requirements: I used a MacBook M2 with 8 GB RAM and 256 GB storage, running macOS Ventura 13.0. This setup provided adequate computational power for preprocessing the NASA C-MAPSS dataset, training neural networks, and running anomaly detection algorithms. No GPUs were needed due to the project's early stage and small dataset (100 engines), but future scalability might benefit from GPU-enabled systems (e.g., NVIDIA GTX 1660 Ti) for faster training on larger datasets.

Software Requirements: The project was developed in Python 3.12.7 using Jupyter Notebook as the IDE. Key libraries included:

- pandas (v2.2.2) for data manipulation.
- scikit-learn (v1.5.0) for standardization (StandardScaler) and data splitting (train_test_split).
- TensorFlow (v2.16.1) with Keras for neural network development.
- matplotlib (v3.9.0) for visualizations.
- NumPy (v1.26.4) for numerical computations.

These were managed via Anaconda, ensuring compatibility across platforms.
Technical Skills Developed: I improved my Python programming, TensorFlow model training (achieving 80% accuracy), and statistical analysis skills for anomaly detection.
Soft Skills Enhanced: I enhanced problem-solving (e.g., handling flat sensor data), time management to meet deadlines (March 15, 2025, to May 10, 2025), and teamwork through collaboration with WireOT Pvt Ltd.
These resources and skills enabled the project's early-stage success, laying a foundation for future enhancements.

2.3 Learning Experiences

In this internship at WireOT Pvt Ltd, I gained valuable technical and professional insights while working on the "EffiMilEngine" project, which focused on real-time health monitoring of military aircraft engines using the NASA C-MAPSS dataset. The experience introduced me to new tools, concepts, and skills that significantly enhanced my capabilities as an Electronics and Communication Engineering student.

One of the key technical learnings was the application of machine learning for time-series data analysis. I explored the use of TensorFlow and Keras to build a multi-layer perceptron (MLP) neural network, learning to design architectures with hidden layers (64 and 32 neurons) and tune hyperparameters like epochs and batch size to achieve an 80% validation accuracy in classifying engine conditions (Healthy or Failing). This deepened my understanding of supervised learning workflows, including data preprocessing with StandardScaler and splitting datasets for training and validation using scikit-learn.

I also gained hands-on experience with anomaly detection techniques, a new concept for me. By implementing a statistical approach (mean + 3 standard deviations) to flag sensor anomalies, I learned to interpret time-series data for predictive maintenance, identifying critical cycles and sensors (e.g., LPC speed, core speed) that signal engine issues.

Visualizing these anomalies using matplotlib improved my data visualization skills, enabling me to create meaningful plots like multi-sensor trends and anomaly detection graphs.

Professionally, I developed stronger problem-solving skills by addressing challenges such as handling flat sensor data (e.g., Sensors 6 and 7), which required selecting alternative sensors (e.g., Sensors 2, 11, 14) to ensure meaningful analysis. Collaborating with the WireOT Pvt Ltd team enhanced my communication and teamwork abilities, as I actively participated in discussions to refine engine health assessments across project phases. Additionally, managing tasks within the internship period improved my time management skills, ensuring timely delivery of analysis and visualizations.

This internship provided a practical understanding of applying AI in aerospace applications, equipping me with skills to tackle real-world engineering problems effectively.

2.4 Challenges and Solutions

During the development of "EffiMilEngine," an AI-driven system for real-time health monitoring of military aircraft engines, several challenges required adaptive problem-solving to ensure project progress, primarily around data quality, model performance, and anomaly detection accuracy. Flat sensor readings in the NASA C-MAPSS dataset, such as turbine temperature (Sensor 6) and pressure (Sensor 7), showed little variability, limiting pattern extraction for health monitoring. Using pandas, sensors with zero standard deviation (e.g., Sensors 1, 18, 19) were identified, and alternative sensors like LPC speed (Sensor 2), core speed (Sensor 11), and HPC outlet temperature (Sensor 14) were selected for robust trend analysis and anomaly detection, as visualized in multi-sensor plots.

Model performance posed another challenge during engine condition classification and anomaly detection. Advanced methods like CatBoost, LightGBM, and Autoencoders underperformed compared to the baseline MLP neural network, struggling with time-series data complexity and noise, yielding lower performance metrics, while the MLP proved more interpretable and effective. A simpler statistical approach (mean + 3 standard deviations) was adopted for anomaly detection, refining the classification pipeline, as summarized below.

Model	Validation Accuracy (%)	Precision (%)	F1 Score (%)	Training Time (Seconds)	Notes
MLP (Final)	80.0	78.0	79.0	10	Effective for classification, used in final analysis
CatBoost	70.0	65.0	67.0	15	Struggled with time-series data
LightGBM	71.0	66.0	68.0	12	Struggled with time-series data
Autoencoder	68.0	62.0	65.0	20	Ineffective for anomaly reconstruction

Table 1 - Performance Comparison of Machine Learning Models for Engine Classification.

The lack of ground truth for RUL estimation complicated anomaly detection validation. This was addressed by leveraging the RUL dataset (RUL_FD001.txt) to set a failure threshold (10 trips) for Failing engines in Phase 3, integrating anomaly counts and initial classifications for a practical evaluation framework, ensuring alignment with the project's goal of delivering an efficient, deployable monitoring system for military aviation. To achieve better results, the anomaly detection threshold was fine-tuned by iteratively adjusting the statistical range (mean + 3 standard deviations) based on feedback from initial tests, ensuring higher sensitivity to critical sensor deviations. Additionally, the classification model was re-evaluated by cross-validating with a subset of the training data, which helped confirm the reliability of the engine health assessments. These steps enhanced the system's ability to identify at-risk engines accurately, supporting the project's objective of proactive maintenance.

Chapter 3 Learning Outcomes and Skills Acquired

3.1 Technical Skills

The "EffiMilEngine" project for real-time health monitoring of military aircraft engines using the NASA C-MAPSS dataset significantly enhanced my technical skills in machine learning, AI, and data processing. I gained proficiency in handling sensor data, applying ML techniques, and exploring deep learning architectures, which are vital for predictive maintenance in aerospace applications.

I learned to apply machine learning and AI for time-series sensor data analysis, using TensorFlow and Keras to build a multi-layer perceptron (MLP) neural network with 64 and 32 neuron layers, achieving 80% validation accuracy in classifying engine conditions (Healthy or Failing). I also explored new deep learning architectures, experimenting with models like Autoencoders, CatBoost, and LightGBM to improve classification and anomaly detection, though the MLP proved more effective for this early-stage project. This deepened my understanding of model selection and tuning.

Data processing skills improved through preprocessing the C-MAPSS dataset with pandas and scikit-learn, standardizing features with StandardScaler, and splitting data for training and validation. I mastered statistical anomaly detection by setting thresholds (mean + 3 standard deviations) to identify sensor anomalies, learning to manage flat sensor readings by selecting dynamic sensors (e.g., Sensors 2, 11, 14).

Additionally, I developed visualization skills with matplotlib, creating plots to analyze sensor trends and anomalies. Working with sensor data enhanced my ability to interpret time-series patterns, equipping me to address real-world engineering challenges in AI-driven systems.

3.2 Personal and Professional Skills

The work experience surrounded me with a vibrant environment that greatly impacted my personal and professional development. The rapid pace challenged me to adjust promptly to new responsibilities and changing priorities, developing my resilience and confidence. I developed the ability to manage my time effectively, juggling several responsibilities to deliver on time without compromising quality, which developed my capability to stay calm under pressure.

Within WireOT Pvt Ltd, I developed my business skills on a routine basis by working with colleagues. Participating in group discussions enhanced my communication skills and helped me to explain ideas clearly, listen attentively, and give constructive feedback. This promoted mutual respect and comprehension, strengthening my team-playing abilities and making me realize the importance of diverse ideas in resolving issues.

The collaborative environment also fostered my people skills and responsibility. I developed close bonds in the team, where I became more empathetic and tolerant, expanding my solutions for workplace issues. Being given responsibilities strengthened my focus and dedication to ensuring my inputs align with team objectives, preparing me to operate in professional environments successfully.

3.3 Knowledge Gained

The internship enriched my knowledge of predictive maintenance in aerospace, specifically through AI and machine learning-based military aircraft engine health monitoring. I learned about the interdisciplinary aspect of aerospace engineering, where domain-specific knowledge, data science, and AI come together to optimize operational safety and efficiency. This experience bridged the gap between theoretical principles of Electronics and Communication Engineering and real-life engineering challenges, making me appreciate practical engineering applications even more.

One of the key learning outcomes was statistical signal processing to analyze time-series data. I applied theoretical practices by computing means and standard deviations to find sensor anomalies, putting thresholds as mean + 3 standard deviations to find deviations such as sensor spikes. This helped me understand how statistical methods guarantee system reliability under operational stress, which is a key factor in aerospace systems where fault detection at an early stage avoids failures.

I also implemented supervised machine learning principles, i.e., neural networks, through training a multi-layer perceptron (MLP) to predict engine conditions (Healthy or Failing) with 80% validation accuracy. This included feature normalization and hyperparameter optimization, incorporating theoretical concepts with the needs of the industry. Moreover, combining anomaly detection with RUL estimation gave a real-world understanding of complete health monitoring systems, making me ready to contribute significantly towards upcoming aerospace projects.

Chapter 4 Reflection on the Internship Experience

The internship with WireOT Pvt Ltd offered a life-changing experience that was largely in line with my aspiration of achieving practical exposure to AI applications in the aerospace sector. I had hoped to have the chance to implement theoretical aspects of Electronics and Communication Engineering in real-life scenarios, and the position delivered on that promise by placing me in a project revolving around predictive maintenance through machine learning. The systematic stages of the project, ranging from data analysis to model creation and outlier identification, enabled me to make meaningful contributions alongside gaining industry-applied skills, which met my initial expectations.

The most valuable part of the internship was the working experience with time-series data and AI-based health surveillance systems. Working as part of a team, I interacted with multiple datasets and tools, and this greatly enhanced my knowledge of how neural networks and statistical approaches can improve operational safety in aerospace. The positive culture of teamwork and constant feedback and discussion helped me develop professionally, especially in communication and problem-solving. This hands-on experience of applying theoretical concepts to practical applications was greatly fulfilling.

Despite this, there are some points that could be improved on. The internship program could have been more formalized in terms of mentorship, like having specific sessions to learn more complex machine learning methods, which would have boosted my model building abilities. Looking back at my performance, I could have taken more initiative in getting reviews on time to smoothen out my way of tackling data analysis problems, like dealing with flat sensor data more effectively.

The internship strongly influenced my career aspirations by enhancing my passion for AI solutions in aerospace engineering. It defined my ambition to have a career in predictive maintenance and system reliability, where I can use AI to solve engineering problems. The experience has encouraged me to further enhance my machine learning and data science skills so that I can contribute to innovative ideas in the aerospace sector.

Chapter 5 Conclusion

The conclusion of this internship reflects a deeply enriching journey that deepened my passion for using AI to solve real-world challenges in the aerospace industry. Working at WireOT Pvt Ltd, I discovered the power of machine learning through hands-on tasks like building neural networks to classify engine health with 80% accuracy and spotting sensor anomalies with statistical methods, such as thresholds set at mean + 3 standard deviations, while also tackling tricky issues like flat sensor data. The collaborative environment taught me how to communicate effectively and solve problems as a team, shaping my perspective on blending theory with practice. I often found myself reflecting on how these experiences brought my classroom learning to life, sparking a sense of purpose. I also learned the importance of resilience, staying motivated despite initial setbacks with complex models. This journey has fueled my desire to dive deeper into machine learning and data science, with a focus on predictive maintenance, and I'm excited to explore advanced models like XGBoost for RUL prediction while seeking opportunities to make a meaningful impact in aerospace engineering, possibly through further research or industry roles.

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