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[ai-powered total predictive maintenance with llm]

[SUTHAREESANAN A/L SARAVANAN]

This report is submitted in partial fulfillment of the requirements for the

Bachelor of [Computer Science (Artificial Intelligence)] with Honours.

FACULTY OF INFORMATION AND COMMUNICATION TECHNOLOGY UNIVERSITI TEKNIKAL MALAYSIA MELAKA

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([Dr. ZURAIDA BINTI ABAL ABAS])

# DEDICATION

To my beloved parents and my family members, I am grateful for the unwavering support and encouragement that you have given to me to complete this project. I also would like to show my appreciation towards the people around me who believed in me and also pushed me forward to succeed in my academic journey. I also extend my heartfelt gratitude to my academic supervisors and peers who through their guidance and insights served as collaborative instrument in the completion of my work. Their faith in my abilities inspired me to strive for excellence in developing this Total Preventive Maintenance application.

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I would also like to extend my gratitude to Ts. Dr. Siti Azirah Binti Asmai whom served as an industrial supervisor, helping me collaborate this project with industries related to it. Her expertise in the industrial related works helped me improve the commercial value of this project, and also pushed me towards adding meaningful components that are needed by companies.

# ABSTRACT

This project advances preventive maintenance for industrial machines by addressing equipment failure prediction and technician support through a dual-component system. The problem of unplanned downtime and inefficient maintenance is tackled using a machine learning model for Remaining Useful Life (RUL) prediction and a large language model (LLM) assistant. The RUL model employs XGBoost with Statistical Process Control (SPC) to predict failure times, processing 148,020 sensor records from a PostgreSQL database, while the Mistral 7B LLM with Retrieval-Augmented Generation (RAG) provides natural language responses to technician queries. Research processes involved data preprocessing, feature engineering (e.g., sensor trends, SPC outliers), model training, and evaluation. The RUL model achieved an RMSE of 246.41 hours, MAE of 173.59 hours, and R² of 0.90, with machine model and age as key predictors, though 8,334 outliers indicate noise challenges. The LLM assistant successfully delivers relevant maintenance insights, enhancing decision-making. This system optimizes maintenance schedules and reduces operational disruptions, with potential for real-time industrial deployment.

# ABSTRAK

Projek ini memajukan penyelenggaraan ramalan untuk mesin industri dengan menangani ramalan kegagalan peralatan dan sokongan juruteknik melalui sistem dua komponen. Masalah masa henti tidak terancang dan penyelenggaraan tidak cekap ditangani menggunakan model pembelajaran mesin untuk ramalan Hayat Berguna yang Tinggal (RUL) dan pembantu model bahasa besar (LLM). Model RUL menggunakan XGBoost dengan Kawalan Proses Statistik (SPC) untuk meramal masa kegagalan, memproses 148,020 rekod sensor dari pangkalan data PostgreSQL, manakala Mistral 7B LLM dengan Penjanaan Dipertingkatkan Pemulihan (RAG) menyediakan respons bahasa semula jadi kepada pertanyaan juruteknik. Proses penyelidikan melibatkan pra-pemprosesan data, kejuruteraan ciri (contohnya, trend sensor, pencilan SPC), latihan model, dan penilaian. Model RUL mencapai RMSE 246.41 jam, MAE 173.59 jam, dan R² 0.90, dengan model mesin dan usia sebagai peramal utama, walaupun 8,334 pencilan menunjukkan cabaran hingar. Pembantu LLM berjaya menyampaikan pandangan penyelenggaraan yang relevan, meningkatkan pengambilan keputusan. Sistem ini mengoptimumkan jadual penyelenggaraan dan mengurangkan gangguan operasi, dengan potensi untuk penggunaan industri masa nyata.

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|  |  |  |
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| **FYP** | **-** | **Final Year Project** |
| **RUL** | **-** | **Remaining Use Life** |
| **SPC** | **-** | **Statistical Process Control** |
| **LLM** | **-** | **Large Language Model** |
| **ML** | **-** | **Machine Learning** |
| **AI** | **-** | **Artificial Intelligence** |

# List of ATTACHMENTS

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# INTRODUCTION

Preventive maintenance is a critical strategy for anticipating equipment failures, thereby minimizing operational downtime and associated costs in industrial settings. This project develops a comprehensive preventive maintenance system comprising two integral components: a machine learning model to predict the Remaining Useful Life (RUL) which is defined as the duration until a machine fails and a LLM-based intelligent assistant to support technicians in decision-making. The RUL prediction model leverages XGBoost, a gradient-boosting algorithm, enhanced with Statistical Process Control (SPC) to address sensor data outliers, ensuring reliable predictions. The technician assistant utilizes Mistral 7B, a large language model, integrated with Retrieval-Augmented Generation (RAG) to provide natural language responses to queries, such as “What caused the failure of Machine X?” by retrieving relevant maintenance logs from a shared database.

The motivation for this project stems from the need to mitigate unplanned outages, which incur significant financial and operational penalties, and to empower technicians with actionable, data-driven insights. By combining preventive analytics with an interactive assistant, the system aims to optimize maintenance schedules and enhance operational efficiency.

## Objectives

The primary objectives of this project are:

* To design and implement a robust XGBoost-based model for accurately predicting the Remaining Useful Life of industrial machines, utilizing sensor data and maintenance records.
* To enhance the RUL prediction model’s reliability by integrating Statistical Process Control techniques for detecting and managing sensor data outliers.
* To develop and deploy a technician dashboard powered by the Mistral 7B large language model with Retrieval-Augmented Generation, enabling natural language query resolution.
* To evaluate the performance of both the RUL prediction model and the technician assistant, assessing their suitability for industrial preventive maintenance applications.

## Scope

This project focuses on developing and evaluating a preventive maintenance system for generic industrial machines, using a dataset of records stored in a PostgreSQL database (AzureTPMDB). The dataset includes telemetry (sensor readings: voltage, rotation, pressure, vibration), failure records, machine metadata (model, age), maintenance logs, and error events. The RUL prediction component employs XGBoost with SPC, implemented in Python with libraries such as SQLAlchemy, pandas, and scikit-learn. The technician assistant utilizes Mistral 7B with a RAG framework, hosted on a web-based dashboard, to retrieve and generate responses from maintenance logs. The scope includes data preprocessing, feature engineering, model training, and evaluation. Limitations include the absence of real-time system deployment, focus on generic machines rather than specific equipment, and qualitative evaluation of the LLM assistant due to the lack of specific metrics. The project excludes hardware-specific optimizations and non-industrial applications.

# literature review

Preventive maintenance has become an important element of industrial engineering, leveraging machine learning (ML) and artificial intelligence (AI) to predict equipment failures and optimize maintenance schedules. This literature review synthesizes key studies on Remaining Useful Life (RUL) prediction, a critical metric for estimating the time until a machine fails, and explores the application of large language models (LLMs) as intelligent assistants for maintenance technicians. Four studies inform the RUL prediction component, while general trends in LLM applications contextualize the intelligent assistant. The review compares methodologies, datasets, models, and findings, identifying gaps that the current project addresses through its novel integration of XGBoost with Statistical Process Control (SPC) and a Mistral 7B-based assistant with Retrieval-Augmented Generation (RAG).

## RUL Prediction Studies

Motrani et al. (2024) investigated RUL prediction for turbofan engines using the NASA C-MAPSS dataset (FD026), which simulates engine degradation with 21 sensor readings across multiple operating conditions [1]. The study compared five supervised ML models: Random Forest, k-Nearest Neighbors (kNN), XGBoost, Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN). Their methodology included rigorous data preprocessing, sensor selection using Lasso regression, and data normalization with MinMaxScaler. LSTM achieved the best performance with an RMSE of 17.98 hours and a PHM08 score of 645.07, followed by XGBoost RMSE: 18.11 hours, PHM08: 794.04. Key sensors included the ratio of fuel flow to static pressure and high-pressure turbine coolant flow. The study’s strength lies in its comprehensive preprocessing and LSTM’s ability to capture temporal dependencies, making it suitable for sequential data. However, the C-MAPSS dataset’s focus on turbofan engines limits its applicability to generic industrial machines, and the study does not address outlier detection, a gap relevant to the current project’s SPC integration.

Al-Refaie et al. (2025) focused on predicting the RUL of milling machine cutting tools using a dataset of 10,000 records with 32 features, including air temperature, process temperature, rotational speed, torque, and tool wear [2]. The authors developed a smart maintenance web application, employing five ML models: Stochastic Gradient Descent (SGD) Regressor, Random Forest Regressor, Decision Tree Regressor, Support Vector Regression (SVR), and Multi-Layer Perceptron (MLP) Regressor. Data preprocessing involved calculating temperature differences and visualizing feature distributions, with a 70/30 train-test split. The MLP Regressor outperformed others, achieving the best fit based on metrics like RMSE, MAE, R², and adjusted R² (exact values not specified). Feature engineering, such as adding temperature difference, enhanced model performance. The web application aligns closely with the current project’s technician dashboard concept. However, the study’s focus on milling-specific features (e.g., tool wear in minutes) and lack of temporal modeling or outlier handling contrast with the current project’s broader scope and SPC approach.

Soualhi et al. (2024), cited in Motrani et al. (2024), proposed an explainable RUL estimation framework for turbofan engines using the C-MAPSS dataset [3]. Their approach combined heterogeneous ensemble ML models (e.g., Random Forest, XGBoost) with prognostic indicators derived from sensor data. The methodology emphasized feature selection to enhance interpretability and used SHAP (SHapley Additive exPlanations) values to explain model predictions. The ensemble model achieved an RMSE of approximately 18.2 hours, slightly higher than Motrani et al.’s LSTM but with improved explainability. The study highlights the value of ensemble methods for robust predictions and the importance of interpretable models in safety-critical applications like aviation. However, like Motrani et al., it focuses on turbofan engines, and the absence of outlier detection strategies limits its relevance to noisy industrial datasets, a challenge addressed by the current project’s SPC features.

Wang et al. (2023), referenced in Al-Refaie et al. (2025), explored RUL prediction for aircraft turbofan engines using the C-MAPSS dataset [4]. Their approach utilized Random Forest with multi-layer perceptron-based feature selection to identify critical sensors, such as high-pressure compressor outlet temperature. The methodology included data preprocessing (e.g., normalization, correlation analysis) and a 80/20 train-test split. The Random Forest model achieved an RMSE of 18.03 hours, comparable to Motrani et al.’s results. The study underscores the effectiveness of feature selection in improving model performance and Random Forest’s interpretability. However, it lacks temporal modeling capabilities and does not address data quality issues like outliers, which the current project tackles through SPC integration.

## Intelligent Assistant with LLM’s

The application of LLMs, such as Mistral 7B, in industrial maintenance is an emerging field. Retrieval-Augmented Generation (RAG) frameworks enhance LLMs by retrieving relevant documents such as maintenance and failure logs to generate contextually accurate responses to technician queries [5]. For example, RAG-based systems can answer questions like “What caused Machine X’s failure?” by combining retrieved logs with natural language generation. Mistral 7B, known for its efficiency in low-resource environments, is well-suited for deployment in web-based dashboards, as proposed in the current project. Unlike traditional rule-based systems, RAG-based LLMs offer flexibility and adaptability to diverse industrial contexts. However, challenges include retrieval accuracy and the need for high-quality document corpora, which the current project assumes are addressed through standard embedding techniques.

# PROJECT METHODOLOGY

The methodology for this project adheres to the CRISP-DM (Cross Industry Standard Process for Data Mining) framework, which provides a structured approach to address the business problem of preventive maintenance through Remaining Useful Life (RUL) prediction using XGBoost with Statistical Process Control (SPC) and the development of a Mistral 7B-based technician assistant with Retrieval-Augmented Generation (RAG). This process spans data acquisition, preprocessing, feature engineering, model training, and evaluation, leveraging data from the AzureTPMDB PostgreSQL database to deliver a robust solution for generic industrial machines.

## Data Acquisition

Data acquisition in this project, aligning with the Data Understanding phase of CRISP-DM, involves retrieving around 800,000 telemetry records containing sensor readings such as voltage, rotation speed, pressure, and vibration, alongside timestamps and machine ID’s from 100 machines, from the Azure Dataset. The dataset was later inputted into which was inserted into a local PostgreSQL database and retrieved using SQLAlchemy in Python. This dataset contains failure logs, machine metadata including model and age, maintenance records with timestamps and components involved in failures, and error logs, all accessed to support both RUL prediction and the intelligent assistant. The comprehensive nature of this data, reflecting real-world industrial operations over an extended period, enables a thorough understanding of machine behavior and forms the foundation for subsequent modeling steps.

## Data Preprocessing

Data preprocessing, corresponding to the Data Preparation phase of CRISP-DM, begins with converting timestamp fields in the telemetry, failures, maintenance, and errors tables into pandas datetime objects to facilitate temporal analysis. The tables are merged based on machine IDs to incorporate the next failure timestamp as the RUL target, with filtering applied to exclude machines without failures and restrict RUL to a range of 0 to 4000 hours. For RUL prediction, a square root transformation is applied to stabilize variance and enhance model performance, followed by normalization of sensor and derived features using StandardScaler to standardize the data. For the LLM assistant, maintenance logs, error reports, and telemetry summaries are extracted as text documents, with embeddings generated using a model like SentenceTransformer to support efficient RAG retrieval, preparing the data for both preventive and assistive tasks.

## Feature Engineering

Feature engineering, also part of the Data Preparation phase, adds extra features to the dataset for RUL prediction by creating temporal features such as the time elapsed since the last maintenance or error in hours, along with binary flags to indicate missing maintenance or error data, enhancing the model’s ability to capture time-dependent degradation. Sensor-derived features are computed, including the mean sensor degradation, change rates for each sensor, and interaction terms that combine sensor changes with error rates, while rolling means and standard deviations are calculated over 6, 12, and 24-hour windows to capture short to medium-term trends. Statistical Process Control is implemented to identify outliers by flagging values that deviate beyond three standard deviations from machine-specific means, generating binary features to improve robustness against noisy data, and the categorical 'model' column is one-hot encoded to account for different machine types, resulting in over 45 engineered features. For the LLM assistant, contextual features are aggregated from machine-specific data, such as the latest telemetry readings and failure history, to provide relevant input for response generation.

## Model Training

Model training, aligning with the Modeling phase of CRISP-DM, involves splitting the data into an 80/20 train-test set with stratification based on RUL quartiles to ensure balanced representation across the range of values, followed by the use of XGBoost with a grid search to optimize hyperparameters including learning rate, maximum depth, subsample ratio, column sampling by tree, and minimum child weight, supplemented by regularization parameters lambda and alpha set to 1.0 and 0.5 respectively. The training process runs for 200 rounds with early stopping after 10 rounds, incorporating sample weights inversely proportional to RUL magnitude to balance high and low RUL instances, and the trained model is saved as 'xgboost\_rul\_spc\_model.pkl' with test data exported as ‘X\_test.csv’ and ‘y\_test.csv’ including datetime and machine ID. For the LLM assistant, the method of fine-tuning of Mistral 7B is done by writing domain specific prompt, implementing RAG by retrieving relevant documents through cosine similarity on embeddings and generating responses with a temperature setting of 0.5 to balance creativity and precision, preparing the system for deployment.

## Evaluation

Evaluation, corresponding to the Evaluation phase of CRISP-DM, for the RUL prediction model includes calculating key metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), R-squared (R²), and Mean Absolute Percentage Error (MAPE) on the original scale, alongside precision, recall, and F1-score using a 100-hour failure threshold for classification purposes to assess preventive accuracy. Visualization is employed as a vital component, with plots generated to compare predicted versus actual RUL, analyse the residuals, display the histogram of residuals, and illustrate predictions with a 95% confidence interval, providing a comprehensive industrial assessment of model performance. For the LLM assistant, evaluation is qualitative assessment, focusing on the relevance, clarity, which are derived from the retrieved context and natural language processing capabilities of Mistral 7B, ensuring the solution meets practical requirements before deployment.

# PROPOSED TECHNIQUE/METHOD

The proposed technique/method for this project, rooted in the Modeling phase of the CRISP-DM framework, combines XGBoost with Statistical Process Control (SPC) to predict Remaining Useful Life (RUL) and integrates Mistral 7B with Retrieval-Augmented Generation (RAG) to provide an intelligent assistance system for technicians. This dual approach leverages a dataset of approximately 800,000 telemetry records from the Azure Dataset integrated into the PostgreSQL database, processed through advanced feature engineering and machine learning techniques, to address preventive maintenance challenges for 100 industrial machines. The methodology emphasizes technical precision, drawing from the implementation details in the provided Python scripts, to ensure robust RUL estimation and actionable technician support via a web based dashboard.

## XGBoost Algorithm with SPC

The RUL prediction component employs XGBoost, a gradient-boosted decision tree algorithm, which constructs an ensemble of trees to minimize a squared error loss function augmented with L1 (reg\_alpha) and L2 (reg\_lambda) regularization terms to prevent overfitting, as configured with values of 0.5 and 1.0 respectively in the ‘train\_model\_postgre.py’ script. The model training process, detailed in the script, utilizes a grid search over hyperparameters including learning\_rate (ranging from 0.05 to 0.2), max\_depth (5 to 6), subsample (0.7 to 0.8), colsample\_bytree (0.7 to 0.8), and min\_child\_weight (3 to 5) to optimize performance, running for 200 boosting rounds with early stopping after 10 rounds if no improvement is observed on the validation set. Sample weights, computed as the inverse of a logarithmic transformation of the square root of RUL are applied to balance the influence of high and low RUL instances, enhancing model sensitivity to critical failure points. The integration of Statistical Process Control, as implemented in the feature engineering step, involves calculating machine-specific means and standard deviations for sensor features (volt, rotate, pressure, vibration) and flagging outliers as binary features when values exceed three standard deviations, a technique that mitigates the impact of noisy data and is reflected in the creation of features like ‘volt\_outlier’ in the script. This hybrid approach, validated through the ‘evaluate\_model.py’ script’s generation of metrics such as RMSE and R², ensures that the model captures both temporal degradation patterns and anomalous sensor behaviors, achieving a reported RMSE of 246.41 hours on the original scale.

## Mistral 7B with RAG

The technician assistance component leverages Mistral 7B, an efficient large language model, enhanced with Retrieval-Augmented Generation to provide context-aware responses, as implemented in the ‘mistral\_query.py’ script. The system operates by hosting a local API endpoint at ‘http://localhost:11434/api/generate’, where natural language queries such as “Why did Machine 42 fail?” are processed with a temperature setting of 0.5 to balance creativity and accuracy, returning JSON responses that form the basis of the assistant’s output. The RAG mechanism, detailed in the script, retrieves relevant context by querying the AzureTPMDB database for machine-specific data, including the latest telemetry averages, recent failures, maintenance logs, and error counts, which are aggregated into a textual context using SQLAlchemy queries. For instance, the ‘get\_machine\_context’ function merges data from the ‘machines’, ‘failures’, ‘errors’, ‘maintenance’, and ‘telemetry’ tables for a given machine ID, while ‘get\_global\_context’ identifies machines with the lowest RUL or highest failure counts from the ‘predictions’ and ‘failures’ tables, respectively. Text embeddings, generated using a model like SentenceTransformer, enable efficient retrieval of relevant documents via cosine similarity, which are then fed into Mistral 7B to generate precise responses integrated with RUL predictions from the XGBoost model. This system is deployed on a Streamlit based web interface, allowing technicians to interact with the assistant and access real-time insights, with the ‘build\_prompt’ function constructing a comprehensive prompt that combines the retrieved context with the user query to ensure informed and actionable advice.

# RESULT AND DISCUSSION

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# CONCLUSION

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# APPENDICES