Enhancing Wind Turbine Longevity: A Comparative Study of Deep Learning and Traditional Machine Learning Techniques for Predicting Remaining Useful Life

MSc Research Project
Programme Name

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MSc Project Submission Sheet

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Supervisor: Dr. Muslim Jameel Syed……..……………………………………………………………….………

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AI Acknowledgement Supplement

1 Practicum

2 Enhancing Wind Turbine Longevity: A Comparative Study of Deep Learning and Traditional Machine Learning Techniques for Predicting Remaining Useful Life

Your Name/Student Number	Course	Date
Busra Sevinc/22183957	Artificial Intelligence	02.09.2023

This section is a supplement to the main assignment, to be used if AI was used in any capacity in the creation of your assignment; if you have queries about how to do this, please contact your lecturer. For an example of how to fill these sections out, please click here.

3 AI Acknowledgment

This section acknowledges the AI tools that were utilized in the process of completing this assignment.

Tool Name	Brief Description	Link to tool
Grammarly	To correct grammar mistakes.	https://app.grammarly.com/

4 Description of AI Usage

This section provides a more detailed description of how the AI tools were used in the assignment. It includes information about the prompts given to the AI tool, the responses received, and how these responses were utilized or modified in the assignment. **One table should be used for each tool used**.

Grammarly	
Correcting Grammar Mistakes	
Grammarly incorrect input	Grammarly correct output

5 Evidence of AI Usage

Sample Input

The demand has gone up for good strategies in the maintenance of wind energy systems due to their increasing complexity and size. Accurate predictions of remaining useful life (RUL) for wind turbine parts are crucial because they help increase operational efficiency which leads to less downtime that is needed for sustainable energy production.

Sample Output

The demand for good strategies in the maintenance of wind energy systems has increased due to their increasing complexity and size. Accurate predictions of remaining useful life (RUL) for wind turbine parts are crucial because they help increase operational efficiency which leads to less downtime that is needed for sustainable energy production.

Enhancing Wind Turbine Longevity: A Comparative Study of Deep Learning and Traditional Machine Learning Techniques for Predicting Remaining Useful Life

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Abstract

The aim of this study is to evaluate how effective deep learning is compared to traditional machine learning in predicting the Remaining Useful Life (RUL) wind turbine components. Various models for predicting wear of damage-sensitive gearbox bearings will be evaluated based on their computational requirements and prediction accuracy, and other relevant factors will also be considered in this research. While evaluating the model performances, the lowest value of Mean Absolute Error (MAE) achieved by Random Forest algorithm because it provides good performance and requires less computational cost. This research increases our knowledge of how to predict when machines will need repairs, and also shows how we can apply these ideas in real world predictive maintenance systems for wind turbines.

1 Introduction

Due to the increasing complexity and size of wind energy systems maintenance, the demand for strategies has increased. Remaining useful life (RUL) estimates are important for improving operational efficiency for wind energy components and helping to reduce losses required for sustainable energy production. According to Wind Europe, sustainability reduces operating costs and environmental impact by increasing the lifespan and efficiency of wind turbines. (WindEurope, n.d). The aim of this study is to investigate new opportunities and challenges brought by developments in artificial intelligence (AI) and especially deep learning. In this study, the performance of deep learning is compared with traditional machine learning methods to predict the Remaining Useful Life (RUL) of wind turbine parts (gearbox bearings and other important components subject to wear and degradation).

Research on wind turbine maintenance prediction has shown that machine learning can increase the accuracy and reliability of RUL predictions. (Teng et al., 2016; Elasha et al., 2019). The aim of this study is to evaluate the effectiveness of various forecasting models in handling complex and active wind turbine data.

The objectives of this research are to:

1. Comparison of the accuracy of deep learning predictions for RUL with traditional machine learning models.
2. How do these models perform in terms of performance and practical use?
3. Explain how predictive maintenance processes can be improved by integrating these technologies with existing maintenance methods.

This study contributes existing scientific understanding by examining various forecasting models and comparing them with each other. This may be useful for wind energy companies to improve predictive maintenance sector.

The study is structured as follows:

- **Chapter 2** examines past research on this topic to gain a better understanding of our technological advances and achievements.
- **Chapter 3** describes the research methodology (data collection, model training, evaluation).
- **Chapter 4** focuses on the design elements and technical framework used in this research.
- **Chapter 5** provides information about the implementation details and computational environment.
- **Chapter 6** evaluates the performance of the predictive models and their results.
- **Chapter 7** concludes the study and provides a summary of its main findings, some limitations, and suggestions for future research.

This research in this area focuses on two main topics: traditional approaches to predictive maintenance with newer methods. We research all of these to prepare for future developments and make them reliable systems.

2 Related Work

2.1 Comparative Evaluation of Deep Learning and Traditional Machine Learning for Predicting Wind Turbine Component RUL

There are two papers that will be important in determining whether deep learning is better than classical machine learning in predicting the RUL of components used in wind turbines. Teng et al. (2016) developed a unique method to characterize RUL in their study with gearbox bearings. It is a combination of neural networks with polynomial integration. This means they do not need long cycle data. This demonstrates the effectiveness of AI in predictive maintenance. However, Elasha et al. use neural networks and regression models to predict RUL using vibration information collected during operation, demonstrating the benefit of improving maintenance strategies.

The accuracy and robustness of deep learning prediction models are on the rise for machine RUL prediction. Xiang et al. (2022) developed the multi-branch convolutional neural network (MBCNN) and automatic differential learning deep neural network (ADLDNN). From multi sensor measurements, the estimated RUL was determined using this formula. Despite the ability to work with NASA`s C-MAPSS dataset and the electromagnetic box containing seismic data, the model is costly and prone to overfitting. (Xiang, Qin, Liu, & Gryllias, 2022). According to Cheng et al. (2020), they developed an integrated framework to predict the RUL substrate by combining Hilbert-Huang transform (HHT), convolutional neural network (CNN), and support vector regression (ε-SVR). Although it consumes a significant amount of computing power and requires parameter fine-tuning, this model produces the lowest prediction error rate (Cheng et al., 2020). Hu, Pi, and Li (2020) improved the accuracy of RUL prediction with a similarity-based deep learning model using long short-term memory (LSTM) networks based on historical data and high-quality authority, but through deviant models. (Hou, Pi, & Li, 2020).

2.2 Integrating Machine Learning and Condition Monitoring for Enhanced RUL Prediction in Wind Turbines: A Comparative Study

Nielsen & Sorensen (2017) and Rezamand (Ed., 2010) have developed comparable methods for estimating the RUL, their techniques differ in that they use machine learning and monitoring data. According to Nielsen & Sørensen (2017), dynamic Bayesian networks and Markov models are used to improve RUL predictions. Our research question is answered by this model, which shows that conservation strategies can be flexible and projects can be adjusted to fit current RUL estimates. On the other hand, Rezamand et al.'s (2021) hybrid model uses SCADA vibration data with Bayesian algorithm to target different operating conditions around wind turbine bearings. This means that by taking environmental factors into account when estimating RUL, predictive maintenance can be more accurate and therefore operational efficiency can be increased. In summary, both studies show how deep learning and traditional machine learning techniques can be used on different parts of wind turbines to improve the prediction and efficiency of maintenance schedules. These advanced predictive models help improve maintenance schedules and optimize the operation of different parts of turbines.

2.3 Advancing Predictive Maintenance: A Comparative Analysis of Deep Learning and Machine Learning Techniques in Wind Turbine RUL Prediction

Pan et al. (2020) and Cheng et al. (2019) have attempted to predict RUL with their methods that provide more accurate estimates of maintenance activities in the industry. According to Pan et al. (2020), the combined use of Deep Belief Networks (DBN) and Self-Organizing Maps (SOM) is optimized through a fruit fly optimization algorithm that reduces noise and abstraction compared to time and frequency domain analysis. The used improvement is particle analysis for RUL prediction accuracy. However, Cheng et al. (2019) incorporated a more sophisticated neuro-fuzzy inference system into their proposed particle filter algorithm. This approach eliminates the particle impoverishment problem and improves RUL determination for carriers. All these methods use a set of techniques to improve the operational efficiency of wind turbines through various maintenance strategies using computational tools such as deep learning implemented by Pan et al. (2020) and Machine Learning combined with fuzzy logic implemented by Cheng et al. (2019).

2.4 Enhancing Predictive Maintenance with Deep Learning: Insights from Wind Turbine Research

In a study by Li et al. (2019), they propose a fault detection method using deep neural networks that can provide precise diagnoses without using target domain data. Therefore, they demonstrate the potential of deep learning in addressing data distribution uncertainties generated from different sources. Additionally, Yücesan and Viana (2020) present a physics-based fatigue model that uses data-driven knowledge integration with physics principles. This is just one example of combining multi-domain knowledge bases through deep learning to improve prediction accuracyIn addition to demonstrating the power and practicality of deep learning systems. It also shows how they can be used to solve complex real-world problems in wind turbine maintenance.

2.5 Machine Leaning and Hybrid Models

Using machine learning and hybrid models, RUL has been estimated using both traditional regression methods and artificial neural networks (ANN) and other machine learning algorithms. For example, Li et al. (2019) used ANN to predict the RUL of rolling element bearings by combining polynomial and exponential regression models. Although this showed higher accuracy than pure regression models, it also depended on data quality and computational requirements (Li, Elasha, Shanbr & Mba,2019). Tayade et al. (2019) used a combination of principal component analysis (PCA), support vector regression (SVR), and random forest (RF) models to identify and select features from seismic data. However, RF was found to be more accurate than SVR, but both models showed computational complexity and generalization issues (Tayade et al., 2019). Elasha et al. (2019) used and regression models to analyze wind turbine gearbox bearing vibration data. They found that ANN performed better. (Elasha, Shanbr, Li, & Mba, 2019). Pandit and Xie (2023) created Sparrow Search Algorithm (SSA) to optimize the parameters for optimization in terms of RF, GPR, and SVM on on high speed shaft bearings using Gaussian process regression model which produces more accurate rates. (Pandit & Xie, 2023).

2.6 Regression-Based Models

Regression-based RUL prediction models use operational data and regression methods to predict machine life. In their study, Vieira et al. (2024) used support vector regression (SVR), gradient boosting regression (GBR), etc. with SCADA system data to develop a RUL prediction framework for wind turbines. This method has very good sensitivity, but it requires a lot of preprocessing steps and also suffers from data uncertainty and generalization (Vieira et al., 2024). Studies like this show that regression methods work well under certain conditions, but a lot of work needs to be done before the data can be processed and validated for different study conditions.

2.7 Research Niche

Previous studies used Various techniques to predict RUL of Wind Turbine components. The objective of this research was to investigate and compare different methods used by these researchers on same dataset.

3 Research Methodology

The aim of this study is to compare deep learning with traditional machine learning to predict RUL for bearings used in wind turbines. This study also aims to propose predictive maintenance strategies that can reduce maintenance costs and increase total energy production by improving operational efficiency.

3.1 Business Understanding

The aim of this study is to compare deep learning with traditional machine learning to predict the RUL value of bearings used in wind turbines. This study also aims to propose predictive maintenance strategies that can reduce maintenance costs and increase overall energy production by improving operational efficiency.

Background and Simulation Process

This study focuses on the important roles of wear- and stress-resistant electrical conductors. This study uses ANSYS to conduct Finite Element Analysis (FEA) and Computational Fluid Dynamics (CFD) to simulate various operating conditions and accurately determine the RUL.

Key Steps in the Simulation Process:

3.1.1 Simulation Considerations:

- **Load and Stress:** Different loads depending on the operating conditions.
- **Lubrication and Wear:** The effect of lubrication quality over time.
- **Vibration and Temperature:** Their effects on conductivity degradation.
- **Historical Data:** Integration of operational history for word simulation.

3.1.2 Simulation Tools and Techniques:

- **MATLAB/Simulink and ANSYS:** For dynamic load modelling and stress analysis.
- **Python/R:** Creating custom simulations to model bearing degradation, leveraging statistical and machine learning libraries for data analysis.

3.1.3 Model Execution and Refinement:

- **Objective Specification:** Defining expected bearing life characteristics for predictions.
- **Simulation Execution:** Creating multiple scenarios to test stress distribution and potential failure points.
- **Validation and Refinement:** Changing simulation parameters based on real-world scenarios to enhance prediction accuracy.

Tools and Techniques

- **ANSYS Workbench:** Serves as the central platform for simulations to provide a complete analysis of bearing performance.

3.2 Data Understanding

Primary data collection includes processes such as familiarizing yourself with the data, identifying data quality issues, discovering initial hypotheses about the data, or identifying appropriate subgroups to generate hypotheses about the hidden data.

3.2.1 **Data Collection:** Simulations from MATLAB/Simulink and ANSYS were used to create a dataset that simulates the operational stresses and deterioration patterns of wind turbine bearings.

3.2.2 **Predictive Maintenance of Wind Turbine Components:** There are 100,000 observations with no missing values in five key features designed to support predictive maintenance modelling of power electronic components. Each column in the dataset is important to understand what affects the remaining life (RUL) of wind turbine components. Here's an overview of the dataset structure:

- **Vibration Level** (float64): It indicates mechanical stability and potential wear by measuring the vibration intensity of turbine components.
- **Rotor Temperature** (float64): It shows the records for rotor temperature, important for monitoring conditions that may affect turbine operation and component life.
- **Operational Hours** (float64): It shows the total operating hours of the turbine, an important factor in assessing component wear and operational stress.
- **Maintenance Frequency** (int64): It indicates the number of maintenance actions performed. This column reflecting the upkeep and preventive care of the turbine.
- **RUL** (float64): This column estimates the remaining useful life of turbine components and it is serving as the target variable for our AI models.

This generated dataset is 3.8 MB in size and provides a solid foundation for exploratory analysis and advanced predictive modelling in our research.

3.2.3 Exploratory Data Analysis:

Figure 1: Histogram of Columns

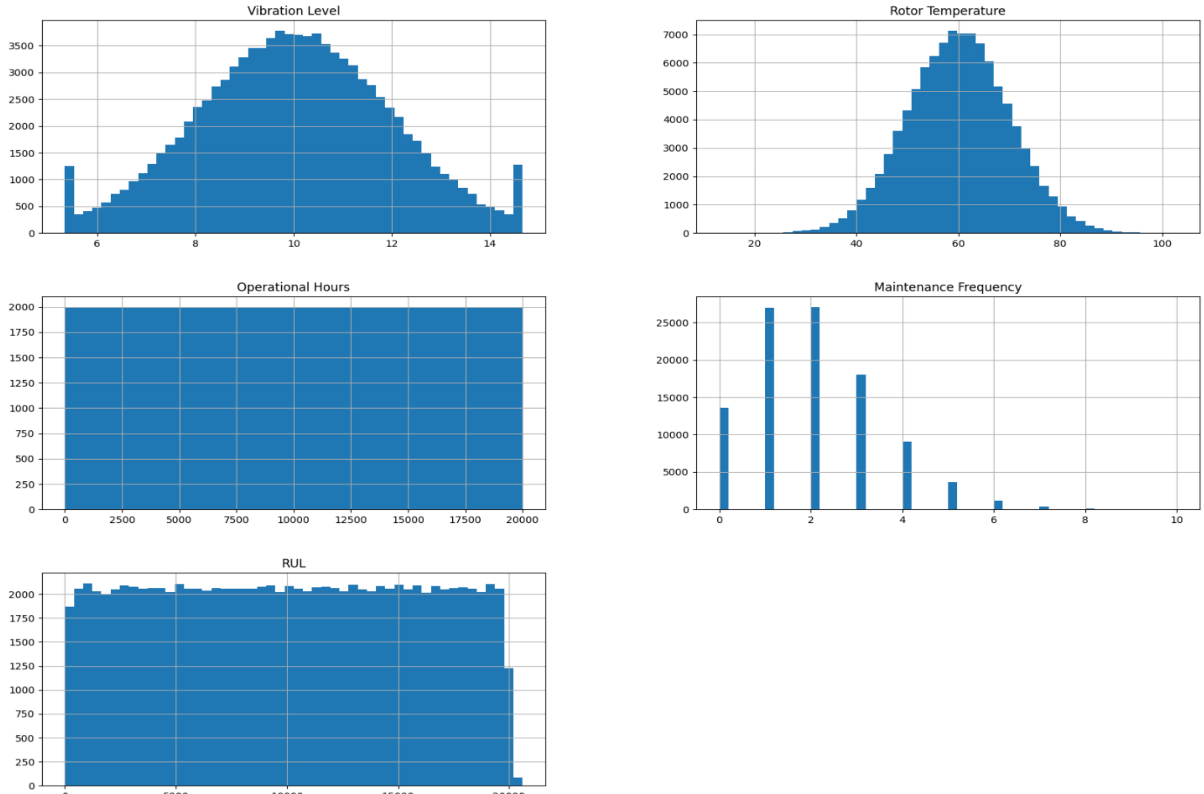


Figure 1 showing the distributions and performance patterns for important variables such as vibration level, rotor temperature, operating hours, maintenance frequency and remaining service life (RUL) is important for understanding the maintenance and efficient operation needs of wind turbines.

Figure 2: The Box Plots

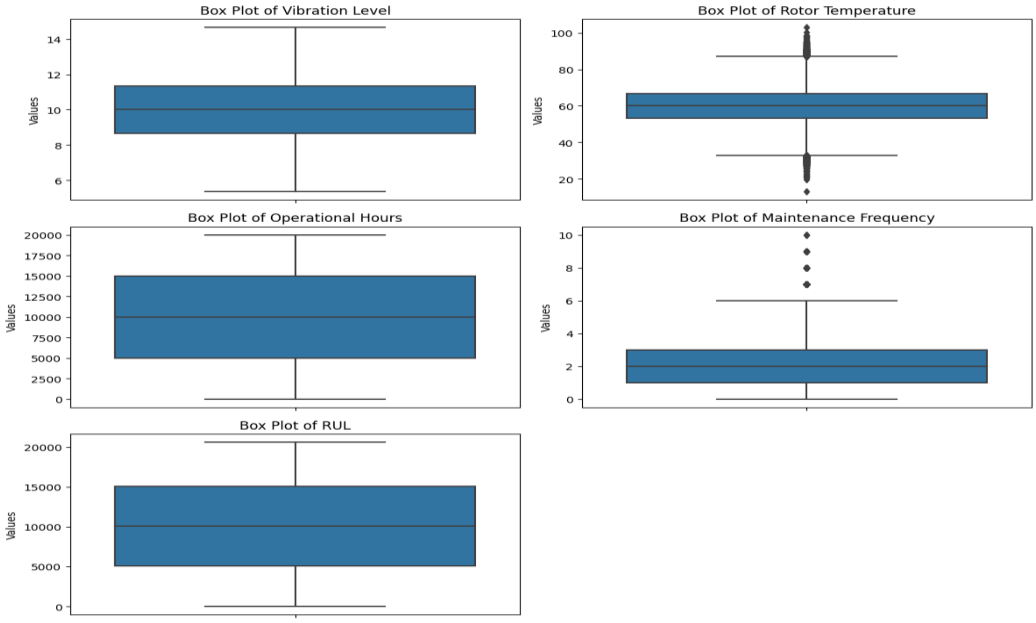


Figure 2 is showing distribution of key columns and showing potential outliers.

Figure 3: Correlation Matrix

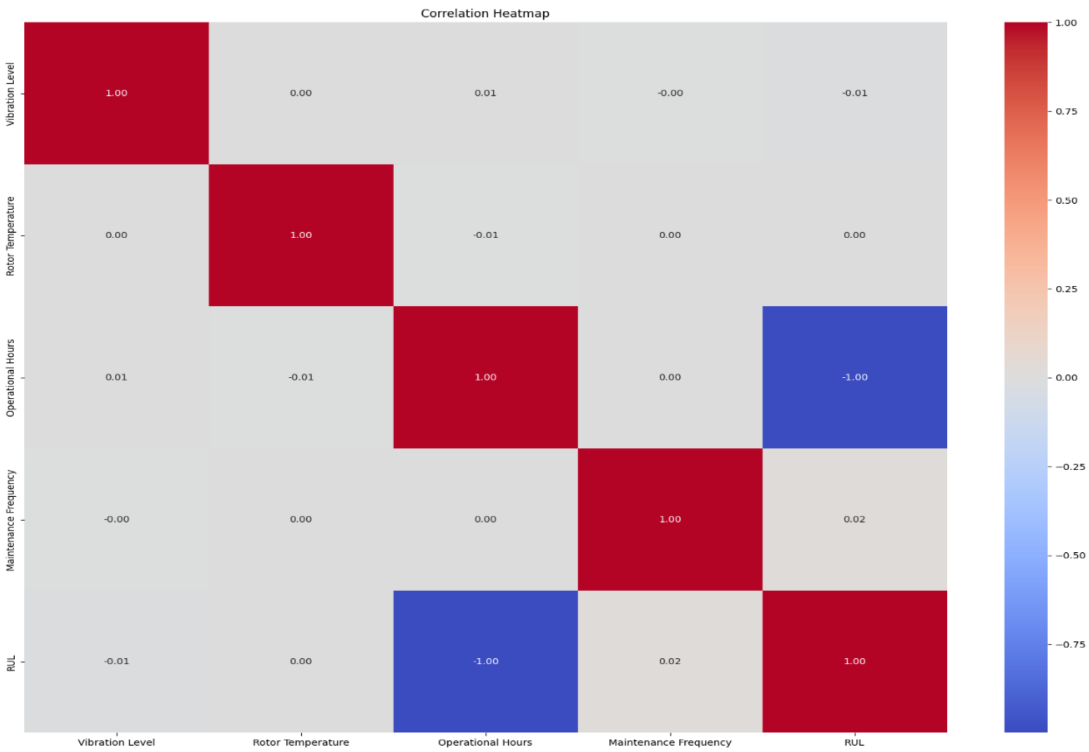


Figure 3 shows the relationship between columns. There is no 1 to 1 relationship between columns except operational hours and RUL which is expected.

Figure 4: Summarize Exploration Steps

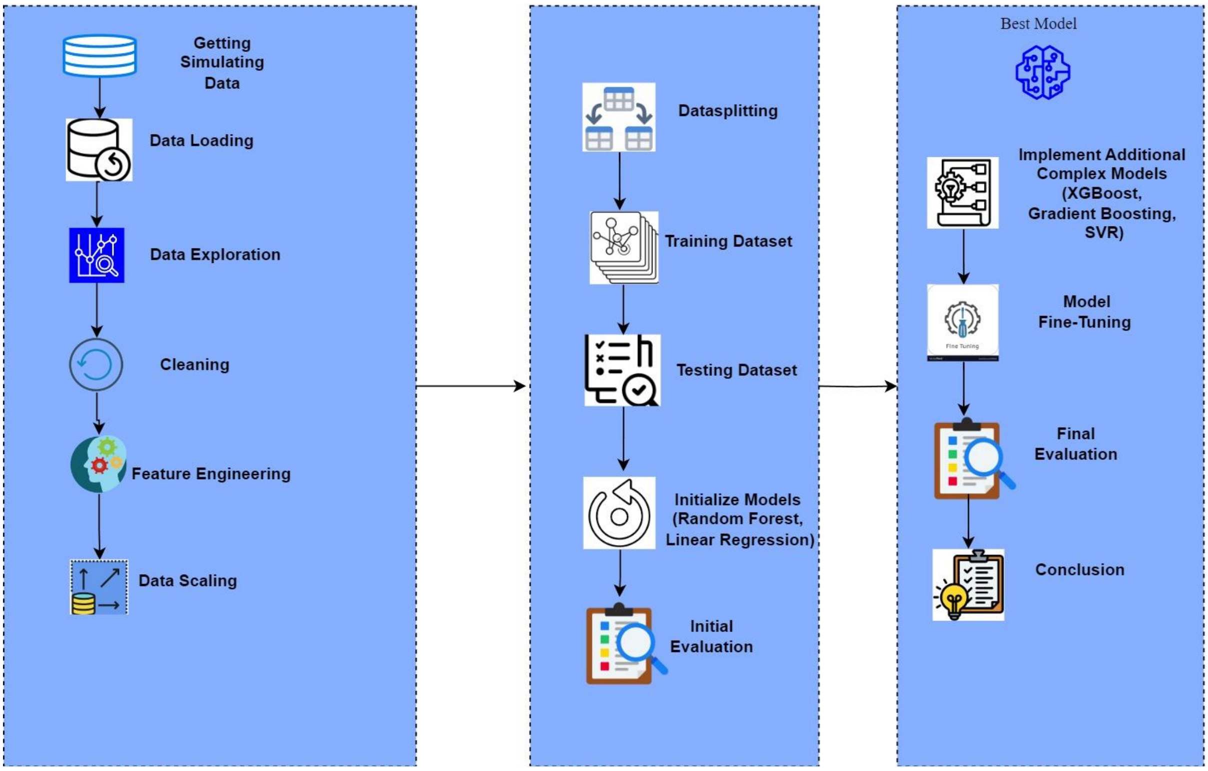


Figure 4 shows the complete predictive modelling process for wind turbine maintenance. It starts with data collection and preprocessing. Then it goes through model generation and evaluation, and finally ends with the selection and refinement of a final model.

3.3 Data Preparation

This step includes all the steps to create the final dataset from the initial raw data. This is done by selecting elements, cleaning the data, creating new variables by manipulating the entire dataset.

- **Data Cleaning:** Handling the outliers and missing values as found during exploratory data analysis.
- **Feature Engineering:** Creating additional attributes to enrich the dataset and hence improve predictive models.
- **Data Scaling and Splitting:** Normalizing the data so that every feature contributes equally. Additionally dividing dataset into training set(s) and test set(s) to prepare for modelling phase.

Figure 5: Data Preprocessing

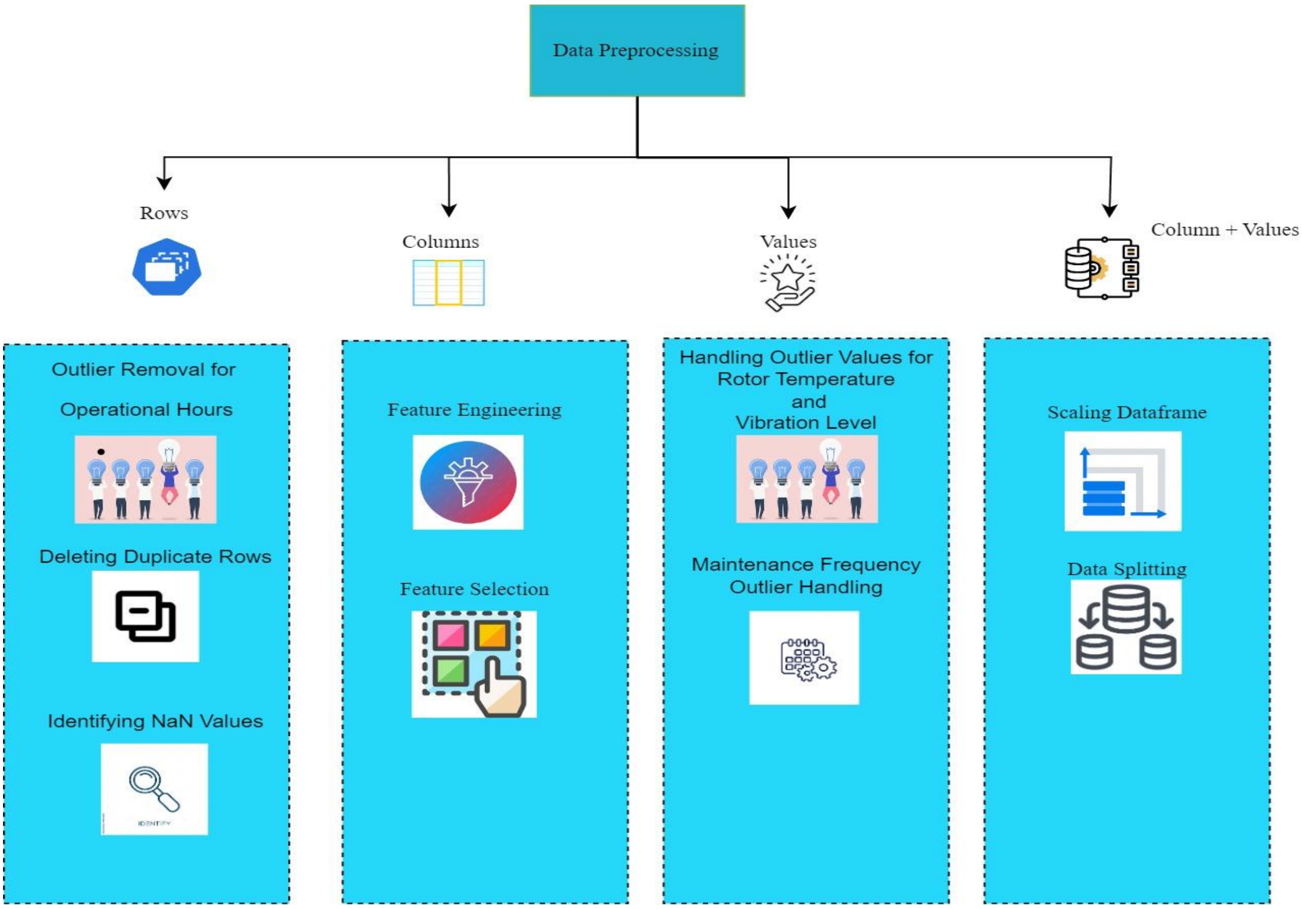


Figure 5 was created for this phase which shows the steps followed during data pre-processing. The diagram includes steps such as dealing with missing values; eliminating duplicates; treating outliers in important variables like operation hours, rotor temperature and maintenance frequency. Finally, data is scaled before splitting into train-test sets to ensure strong model training and evaluation.

3.4 Modelling

Different types of modeling methods are chosen and to find best result hyperparameter optimization is applied on best model.

- **Model Training:** Various machine learning models and deep learning models used for model training step to compare and find best performing model.
- **Hyperparameter Tuning:** GridSearchCV library used to find best hyperparameters on models.

3.5 Evaluation

In evaluation step, metrics such as MAE, MSE, RMSE, and R^2 can be used. In this study only MAE used because the results are more distinguishable from each other than other metrics.

- **Performance Evaluation:** Mean Absolute Error (MAE) is main Evaluation metric.
- **Model Comparison:** Comparison of models by MAE. The lower MAE means better accuracy of RUL.

Mean Absolute Error (MAE)

- **Description:** Measures the average absolute difference between predicted values and actual observations.
- **Formula:** $\frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$
- **Interpretation:** A MAE of 0 indicates perfect accuracy. Higher values signify larger errors.

4 Design Specification

4.1 Techniques and Architecture

The prediction model for determining the remaining useful life (RUL) of wind energy components is based primarily on a robust methodology that includes external control, performance and model selection at its best through training and evaluation.

4.1.1 Handling Outliers: The outlier detection approach uses a statistical threshold, where elements above three standard deviations from the mean are considered outliers and are removed. This ensures that the method and fits the prediction models.

- **Rotor Temperature and Vibration Levels:** Each variable was carefully examined to extract different data. This was done by calculating the addition and subtraction of twice the standard deviation and discarding values that exceeded this limit.
(mean ± 2 standard deviations).
- **Operational Hours:** In this step a logarithmic scale was previously used to transform the operational hour data to better examine skewness and further refine the data by removing outliers beyond the 1st and 99th percentiles.

4.1.2 Feature Engineering: This step creates new features that represent the interaction of various operating parameters, such as increasing rotor temperature and vibration levels, to quantify the effect of RUL.

4.1.3 Visualisation of Clean Data: With removal of Outliers, vibration level and rotor temperature come close to normalized representation. Other features are slightly changed compared to their previous plots.

Figure 6: Visualization of Clean Data

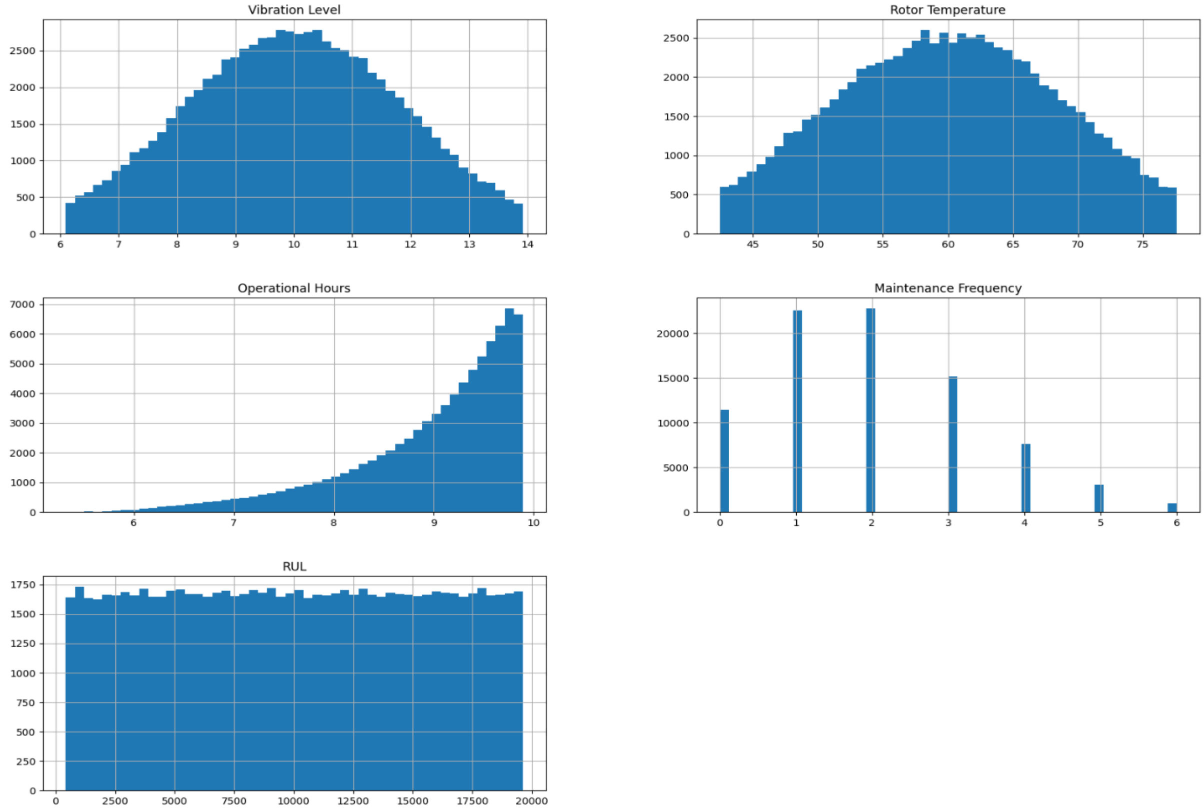


Figure 6 shows the state after the correct outliers are deleted.

4.2 Model Selection and Hyperparameter Tuning

This section describes simple machine learning and deep learning techniques as well as computational methods used to estimate RUL for wind turbine. Before training the models, all features are normalized to ensure that the data scale is the same across all models.

4.2.1 Standard Scaling: Because some models can operate on a scale, all numerical functions are normalized so that the mean and unit variance are equal, thus the weights of the inputs are equal.

4.2.2 Ensemble Methods

- Linear Regression: This is a traditional machine learning technique, works like a real model but is part of an ensemble learning strategy where its predictions are combined with other models, hence improving predictive performance and stability.
- Random Forest: It is a classic machine learning clustering technique that combines predictions from multiple decision tree models to improve accuracy when dealing with overfitting problems.
- Gradient Boosting: This is a powerful technique for ensembles creating new models that correct the errors made by pre-trained models each time, thus effectively reducing the variances and variances.

4.2.3 Advanced Machine Learning and Deep Learning Models

- **Support Vector Regression (SVR):** SVR works well with non-linear data by using kernel functions that handle higher dimensional spaces necessary for complex datasets.

- **XGBoost Regression:** Known for its power and performance in the Gradient Boosting family, XGBoost can handle a variety of data and distributions well, making it ideal for classification and regression tasks.
- **Long Short-Term Memory (LSTM) Networks:** LSTM was specifically chosen because it can capture long-term dependencies in time series data points, which are important for accurately estimating RUL based on historical sensor readings.

4.2.4 Hyperparameter Tuning

Hyperparameter tuning is applied to minimize MAE value by searching combination of hyperparameters with GridSearchCV. By finding optimal hyperparameters, the lowest MAE achieved.

5 Implementation

5.1 Environment Evaluation

The study was conducted using a personal computer with the following specifications:

- **Operating System:** Windows 11 Home 64-bit (10.0, Build 22621) (22621.ni_release.220506-1250), with regional language settings in English.
- **System Manufacturer:** Asustek COMPUTER INC.
- **System Model:** ASUS TUF Dash F15 FX517ZE_FX517ZE
- **BIOS Version:** FX517ZE.315 (type: UEFI)
- **Processor:** 12th Gen Intel(R) Core(TM) i5-12450H (12 CPUs), operating at ~2.0GHz.
- **Memory:** A total of 16GB (16384MB) RAM was installed with 16006MB available for OS tasks.
- **Page File Memory:** A total of 10116MB was used, with 14545MB available.
- **DirectX Version:** DirectX 12

5.2 System Requirements

- **Operating System:** Compatible with Windows, macOS, or Linux.
- **Processor:** Intel i5 or equivalent.
- **RAM:** 8 GB or higher recommended.
- **Storage:** At least 10 GB of free space for data handling and processing.

5.3 Python Environment

The project is implemented in Python, and the following versions of Python and libraries are used:

- **Python Version:** 3.8 or newer Python 3.8 supports all required libraries and features used in this project, offering improved module handling and stability.
  Key Libraries and Versions
- **NumPy (1.19.5):** Provides support for large, multi-dimensional arrays and matrices, along with a large collection of mathematical functions to operate on these arrays.
- **Pandas (1.1.5):** Used for data manipulation and analysis, providing data structures and operations for manipulating numerical tables and time series.
- **Matplotlib (3.3.4):** A plotting library for creating static, interactive, and animated visualizations in Python.

- **Scikit-Learn (0.24.1):** Used for machine learning and statistical modelling including classification, regression, clustering, and dimensionality reduction**.**
- **TensorFlow (2.4.1):** An end-to-end open-source platform for machine learning to easily build and deploy ML powered applications.

5.4 Machine Learning and Deep Learning Standard Hyper Parameter Settings

Table 2 shows the different machine learning and deep learning models used in this study and their set of hyperparameters. This is a set of values that should be tuned for optimal performance based on the model used.

Table 2: Details the Standard Hyperparameters Used Across Various Machine Learning and Deep Learning Models

Model	**Hyperparameters**	**Tuning**
Random Forest	n_estimators	100
	max_depth	Not specified
	min_samples_split	Not specified
	min_samples_leaf	Not specified
	max_features	Not specified
	random state	42
Linear Regression	n_estimators	100
	max_depth	Not specified
	min_samples_split	Not specified
	min_samples_leaf	Not specified
	max_features	Not specified
	random state	42
Gradient Boosting	n_estimators	100
	learning_rate	0.1
	max_depth	3
	random state	42
	min_samples_split	Default
	min_samples_leaf	Default
Support Vector Regression (SVR)	kernel	\`rbf\`
	C	100
	gamma	0.1
	epsilon	0.1
XGBoost Regression	n_estimators	100
	learning_rate	0.1
	max_depth	5
	alpha	10
	colsample_bytree	0.3
LSTM	units per layer	[50,25]
	epochs	100
	batch_size	20
	dropout	0.2
	input_shape	Specified per dataset dimensionality

Models were implemented using the hyper parameter values shown in Table 2.

5.5 Hyperparameter Tuning

This section of the report explains how we use hyperparameters to optimize our machine learning models.

5.5.1 GridSearchCV Optimization

The GridSearchCV technique from scikit-learn library was used to explore the parameter sets for the Random Forest Model.

Parameter Grid:

- n_estimators: [50, 100, 200]
- max_features: ['auto', 'sqrt', 'log2']
- max_depth: [None, 10, 20, 30]
- min_samples_split: [2, 5, 10]
- min_samples_leaf: [1, 2, 4]

Optimization Results:

- **Best Parameters:**
  - n_estimators: 200
  - max_depth: 20
  - max_features: 'auto'
  - min_samples_leaf: 1
  - min_samples_split: 2
- **Best MAE Score:** 0.0015

The grid search process tested a total of 324 different combinations, and the selected configuration minimized the absolute error (MAE).

6 Evaluation

6.1 Performance Measures and Their Appropriateness

In this study, we used MAE as the main evaluation criterion to measure the accuracy levels in estimating the RUL of wind turbine parts.

6.2 Experiment 1: Linear Regression

Figure 7: Linear Regression Result

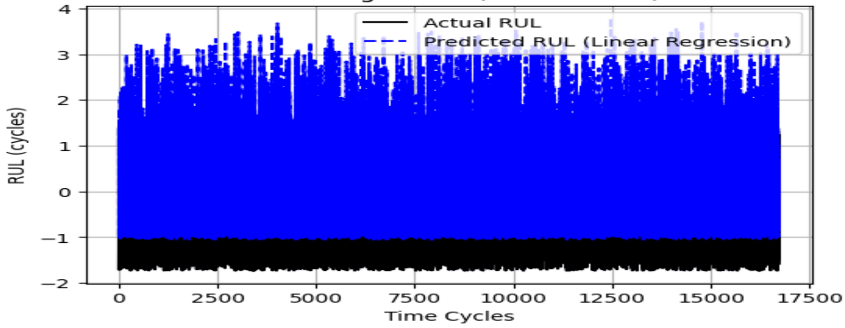
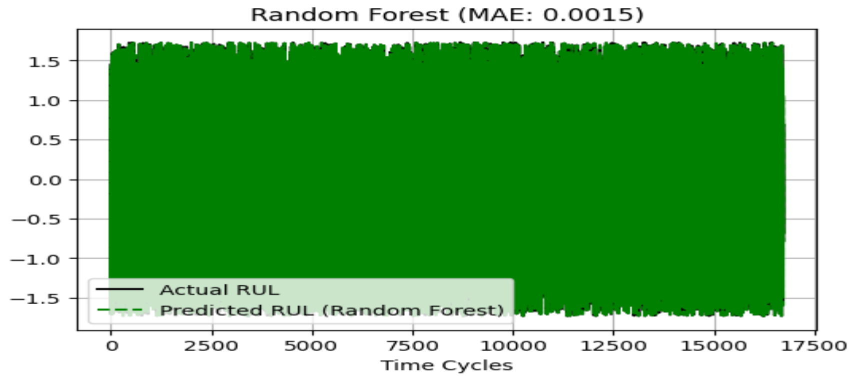


Figure 7 shows that there is a significant difference between the predicted RUL and the actual RUL, especially on the uptrends. Due to this high MAE, linear regression may not be able to capture the latent factors properly.

6.3 Experiment 2: Random Forest

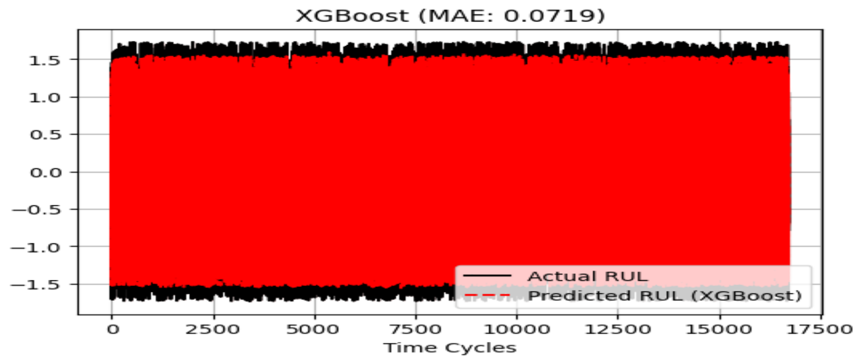
Figure 8: Random Forest Result



According to Figure 8, a Random Forest has the lowest MAE value. The predictions are very close to the true RUL for all time variables, indicating that the model captures the complex patterns and relationships in the data well.

6.4 Experiment 3: XGBoost Regressor

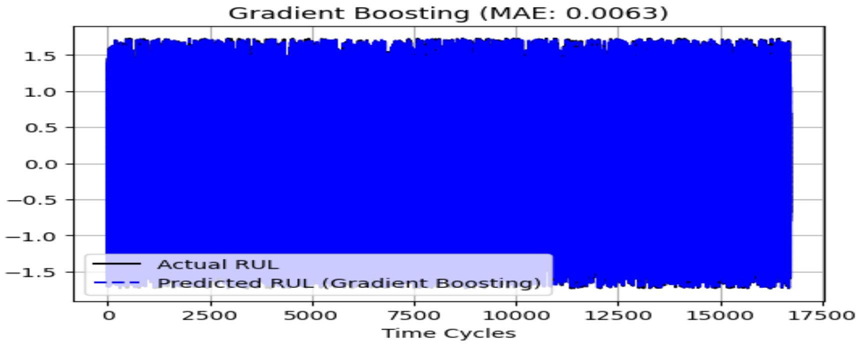
Figure 9: XGBoost Regressor Result



According to Figure 9, XGBoost shows low MAE performance. While it is not as good as Random Forest in terms of MAE, it is better than linear regression.

6.5 Experiment 4: Gradient Boosting

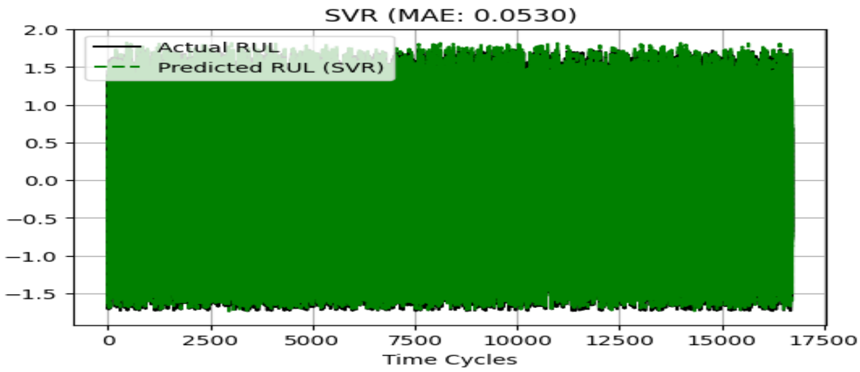
Figure 10: Gradient Boosting Result



According to Figure 10, despite the MAE is higher than Random Forest MAE value, this model is still considered good. The graph shows that the Multiplier is approaching the true RUL with some minor deviations visible, but the performance is quite accurate.

6.6 Experiment 5: SVR (Support Vector Regression)

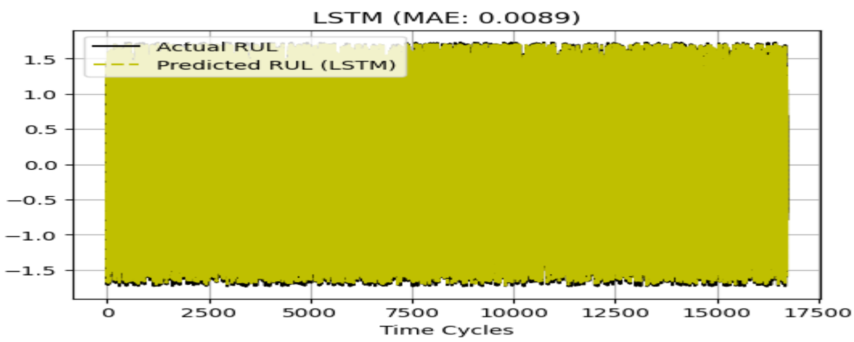
Figure 11: SVR Result



According to Figure 11, Random Forest and Gradient Boosting has a lower MAE result than SVR.

6.7 Experiment 6: LSTM

Figure 12: LSTM Result



According to Figure 12, The LSTM model was not preferred because it could not reach the sensitivity of the Random Forest model.

6.8 The performance metrics for each predictive model

Table 3: Table Summarizing the Performance Metrics for each Predictive Models

Model	MAE
Linear Regression	0.3254
Random Forest	0.0015
Gradient Boosting	0.0719
Support Vector Regression	0.0063
XGBoost	0.0530
LSTM	0.0089
Random Forest	0.0015

Table 3 shows the performance on MAE. These figures demonstrate the accuracy and precision of wind turbine component RUL prediction.

The optimized random forest model achieved the best result with a MAE of 0.0015. This means that the model made the correct prediction for all cases of the dataset it worked on.

Figure 13: Mean Absolute Error of Various Models

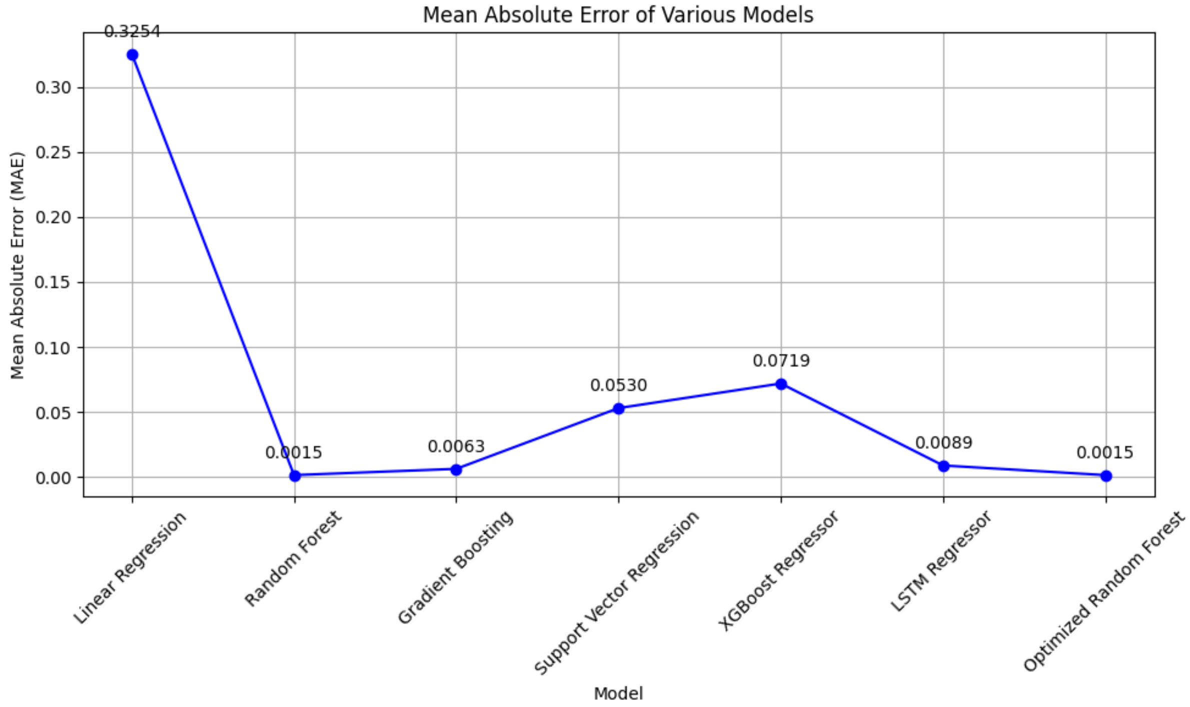


Figure 13 shows the MAE for various forecast models and shows the average error of the forecasts:

- **Linear Regression (MAE: 0.3254)** has the highest error, indicating poor performance.
- **Random Forest (MAE: 0.0015)** Original and optimized have shown the lowest error indicating their high precision.
- **Gradient Boosting (MAE: 0.0063)** and **LSTM Regressor (MAE: 0.0089)** also perform well with low errors.
- **Support Vector Regression (MAE: 0.0530)** and **XGBoost Regressor (MAE: 0.0719)** exhibit moderate errors.

The optimized random forest is considered as the best model as it has the lowest possible error and can be used for accurate predictions.

6.9 Feature Importance

Figure 14: Feature Importance

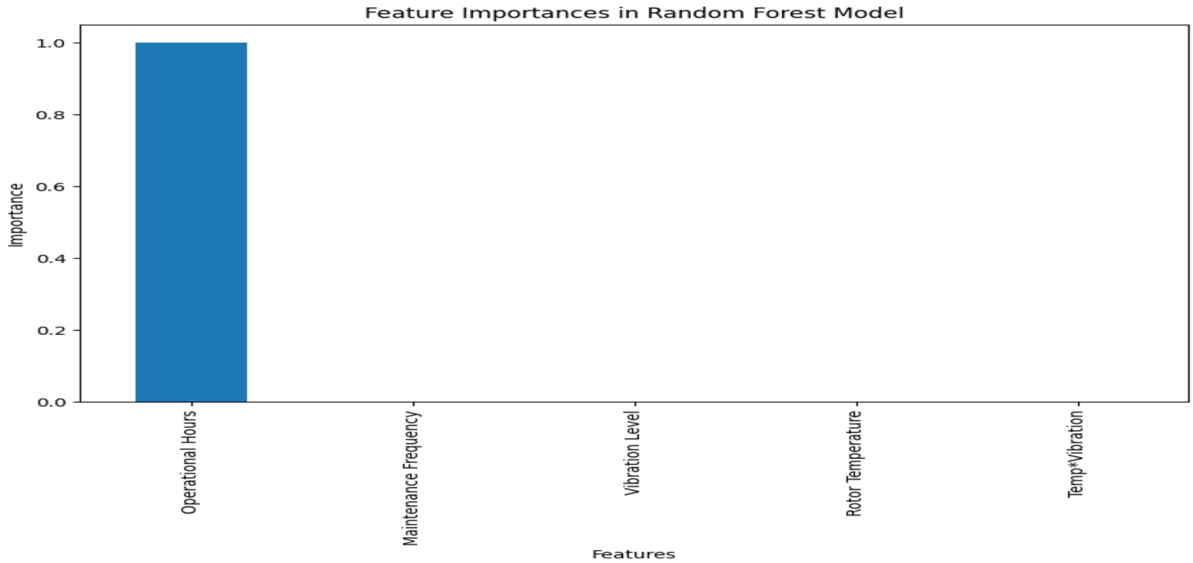


Figure 14 shows the feature importance in the random forest model predicting RUL of wind turbine components. According to the chart, "Operational Hours" is the most important predictor; how long a part has been operating gives information about its remaining lifespan. This bar chart shows what drives this model's decision and shows areas for improvement by evaluating different features.

6.10 Method Utilization to Address the Research Question Discussion

We used a various method to determine whether deep learning is effective in predicting RUL in wind turbine components compared to traditional machine learning methods. We do this by creating large simulation data sets that reflect the operating conditions of wind turbine components under various loads. This study also evaluates the predictive power of each method based on MAE. Additionally, this process includes fitting the models through hyperparameter tuning and validating the performance on different hyperparameters for a lower MAE score, hence better accuracy. So what we've done here is taken a systematic approach that allows us to gain useful insights into our predictive maintenance strategies to improve the efficiency of sustainable wind energy systems. In this way we compared various machine learning and deep learning models on same dataset to find which method performs best for predicting RUL.

7 Conclusion and Future Work

7.1 Conclusion

In this study, RUL prediction in wind turbine components was investigated using machine learning and deep learning models. Different forecast models were evaluated using large data sets to assess how well they perform to estimate RUL of wind turbine components.

The aim of this research is to improve the accuracy of predictive maintenance models and increase the lifespan of wind turbine components through advanced predictive analytics. This study included different models and compared them in terms of performance using MAE metric. The random forest model has best prediction accuracy with the lowest MAE and achieves the best performance.

7.2 Key Findings

1. **Model Performance**: The optimized random forest model turned out to be the most accurate model, demonstrating its reliability and robustness in controlled environments.
2. **Technological Implications**: The results showed that incorporating machine learning into maintenance policies is crucial as it significantly increases efficiency and minimizes downtime.
3. **Limitations**: Despite its success, some limitations are acknowledged that may hinder scalability or global applicability, such as the reliance on large amounts of high-quality data and computing power.

7.3 Future Work

Future research can contribute significantly to current research by considering the following areas:

1. **Real-Time Data Processing**: The developed models must be able to cover the dynamic structure of the real data to be more sensitive than the systems used to predict errors before they occur.
2. **Commercialization Potential**: The optimized random forest model is effective; it can also be used in various industries within the renewable energy sector. In-depth market research and testing under real conditions on a small scale is an important part.
3. **Ethical and Sustainable Use**: In future planning, the ethical issues of artificial intelligence need to be re-evaluated in organizational environments in order to develop smart and sensitive solutions that comply with world standards and norms.

Subsequent studies will expand on the fundamental work of this project by examining these areas and ultimately expanding the field of predictive research into future energy savings to improve efficiency, reliability, and cost.

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