Comparative Study of Machine Learning Techniques for Remaining Useful Life Estimation in Simulated Mini Factory Environment

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Abstract: Predictive maintenance (PdM) has become one of the most effective approaches for enhancing the longevity of industrial assets and minimizing the costs associated with their failure. This study aims to design and evaluate different machine-learning algorithms to determine the RUL of industrial machines based on temperature, vibration, and RPM sensors. The assessed models involve Linear Regression, Random Forest Regressor, Decision Tree Regressor, K-Nearest Neighbors Regresor, and Gradient Boosting Regressor. To establish real-life industrial environment and to put our method of predictive maintenance under realistic setting, the mini factory environment with use of Arduino was created. This setup involves a DC motor with temperature, vibration, and RPM sensors to monitor its state. The DC motor is chosen as one of the industrial machinery components that must be monitored, and the sensors record the parameters of its functioning. This mini factory environment allows for controlled experiments and data collection without disrupting actual production lines. In the preprocessing of data, there are some techniques to help our model become more predictive, which we call feature engineering and hyperparameter tuning in the model. Model performance was quantified using the Mean Squared Error, Root Mean Squared Error, R-squared score, and cross-validation score. Experiments prove that to accurately predict RUL, the best ensemble learning methods applied are gradient boosting and Random Forests. This research benefits industries as it assists PdM in providing an accurate estimation of the remaining useful life of industrial machinery using sensor data, thus reducing the time and cost of maintenance and increasing productivity.

Keywords: Predictive Maintenance (PdM), Remaining Useful Life (RUL), Machine Learning, Sensor Data, Ensemble Learning

I. INTRODUCTION

The reliability and effectiveness of industrial equipment are critical when it comes to the effective and continuous running of the processes. Predictive maintenance (PdM) is a method of maintenance that is goes in line with the concept of preventive maintenance where the objective is to maximize the maintenance performance by estimating the RUL of equipment in order to predict the possibility of failure. This research aims at working with datasets collected from temperature, vibration and RPM sensors of industrial machines to build and compare various ML models for estimating RUL. Its purpose is to achieve the highest effectiveness of maintenance activities, minimize failure costs and improve the efficiency of industrial equipment.

Conventional maintenance methods can be divided into two; that is; the preventive maintenance and the reactive maintenance. Preventive maintenance involves scheduled maintenance of machines at regular intervals or based on usage, while reactive maintenance refers to interventions after a failure has occurred. Both methods have significant drawbacks. Preventive maintenance can lead to unnecessary maintenance and increased costs, whereas reactive maintenance can result in production losses and high costs due to unexpected failures.

To overcome these challenges, Predictive maintenance (PdM) employ sensors and machine learning techniques that enable the evaluation of the status of machines and identify possible breakdowns. This will help to allow maintenance actions only when required, thus eliminating unnecessary maintenance expenses and manufacturing downtime.

Different machine learning methods were used in this work with the goal of predicting the RUL of industrial machines. These models include Linear Regression, Random Forest Regression, Decision Tree Regression, K-Nearest Neighbors Regression, and Gradient Boosting Regressor. The performance of these models was compared using various evaluation metrics, and the best-performing model was identified

II. METHODOLOGY

This section presents the methodology employed in this study to achieve the aforementioned objectives. It encompasses the experimental setup, dataset details, data preprocessing and feature engineering process, machine learning model selection, and evaluation metrics.

A. Experimental Setup

To establish real-life industrial environment and to put our method of predictive maintenance under realistic setting, the mini factory environment with use of Arduino was created. This setup involves a DC motor with temperature, vibration, and RPM sensors to monitor its state. The DC motor is chosen as one of the industrial machinery components that must be monitored, and the sensors record the parameters of its functioning. This mini factory environment allows for controlled experiments and data collection without disrupting actual production lines.

B. Dataset

This study utilizes two distinct datasets collected from an industrial machine. Both datasets comprise 10,000 rows of data. The first dataset, contains data gathered during the machine's normal operating conditions. The second dataset, encompasses data recorded during a period when the machine experiences a gradual fault. Each dataset includes three main features:

RPM (Revolutions per Minute): This feature defines the number of cycles of rotation of the moving parts of the machine per unit of time and is a measure of the condition of the machine and its performance.

Temperature: This feature monitors the temperature conditions within the machine. Unusual temperature fluctuations can often be indicative of potential malfunctions.

Vibration: This feature measures the vibration levels experienced by the machine. Elevated vibration levels typically signify mechanical issues such as imbalances or misalignments.

By combining these two datasets, a comprehensive dataset is created, encompassing both normal and faulty operational states. This combined dataset serves as the foundation for training and evaluating various machine learning models to accurately predict the Remaining Useful Life (RUL).

C. Data Preprocessing and Feature Engineering

During the data preprocessing step the two datasets are combined into one new dataset a new column labeled ‘label’ is created to differentiate between normal and faulty operating conditions. Subsequently, the dataset is checked for missing values, and it is confirmed that there are no missing entries.

To improve the forecast performance of the data, new features are created out of the raw sensor data based on monitoring time. These features include rolling means, rolling standard deviations and the percentage changes calculated over a moving average of three consecutive observations on RPM, temperature and vibration respectively. Rolling statistics are used to track variations and trends in the data that are specific to a particular location, whereas percent changes show the numeric difference between two data points. These engineered features are incorporated in the model in an attempt to enhance its comprehension of the degradation process of the machine so as to obtain a better estimation of its RUL.

D. Data Normalization

Another approach that is used in the process of preparing the data involves making adjustments to the datasets so as to ensure we obtain an improved data set for training of the machine learning models. In this case, the feature data comprises RPM, temperature, vibration, and new features introduced by converting the time series data to time-based features such that they are normalized using MinMaxScaler. MinMaxScaler makes the scaling of all four feature values into the range 0 to 1 which helps in the equal treatment of features having different scales and also assists in fast convergence of the Model.

E. Model Training and Hyperparameter Tuning

Five distinct machine learning models are utilized in this project for RUL prediction:

1) Linear Regression: This model assumes a linear relationship between the predictor variables (sensor data) and the target variable (RUL), making it a simple and interpretable approach.

2) Random Forest Regressor: This ensemble learning method constructs multiple decision trees and averages their predictions, enhancing accuracy and mitigating overfitting. Each tree is trained on a different subset of the data, promoting diversity and robustness in the model.

3) Decision Tree Regressor: This model recursively partitions the data based on feature values to create a tree-like structure for prediction. While capable of capturing complex relationships, decision trees are prone to overfitting, necessitating careful pruning or ensemble techniques.

4) K-Nearest Neighbors Regressor: This non-parametric method predicts the RUL based on the average of the k-nearest neighbors in the feature space. It is well-suited for cases where similar operational conditions lead to similar failure patterns but may struggle with high-dimensional data.

5) Gradient Boosting Regressor: This ensemble technique sequentially builds a series of models, each correcting the errors of the previous one. It is known for its high predictive accuracy and ability to capture complex patterns and interactions in the data.

Hyperparameter tuning is performed using GridSearchCV for Random Forest and Gradient Boosting Regressor models to identify the optimal parameter combinations that yield the best performance. This process involves systematically searching through a grid of hyperparameters and selecting the best set based on cross-validation scores.

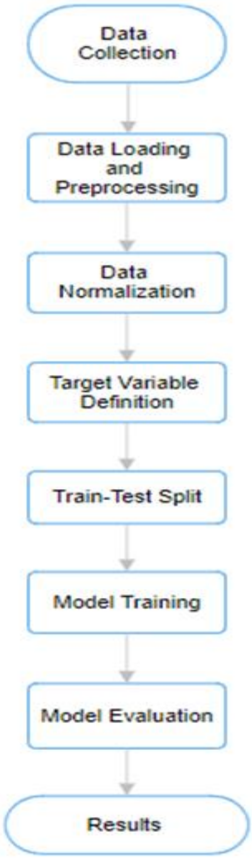

Fig 1. Flowchart of the predictive maintenance process using machine learning

F. Model Evaluation

The performance of each machine learning model is assessed using the following metrics:

Mean Squared Error (MSE): This metric quantifies the average squared difference between the predicted and actual RUL values.

Root Mean Squared Error (RMSE): The square root of the MSE, providing an error measure in the same units as the target variable.

R-squared (R^2) Score: This score represents the proportion of variance in the dependent variable (RUL) that can be explained by the independent variables (sensor data).

Cross-Validation (CV) Score: This score evaluates the model's ability to generalize to unseen data by averaging its performance across multiple folds of the dataset.

III. RESULTS

In this research, five ML models namely Linear Regression, Random Forest, Decision Tree, K-NN and Gradient Boosting were trained the results of which were analyzed in terms of their capability to estimate the industrial machines RUL. To assess the performance of the models several indicators including Mean Squared Error (MSE), Root Mean Squared Error (RMSE), the R-squared (R^2) score, and the Cross Validation (CV) score were used. The accuracy of the models is derived directly from their R^2 scores, representing the proportion of variance in the RUL that is explained by the model.The results are summarized in Table 1:

Model	MSE	RMSE	R^2	CV
Linear Regression (LR)	1,67	1,29	0,20	0,22
Random Forest (RF)	0,08	0,28	0,96	0,96
Desicion Tree (DT)	0,14	0,37	0,93	0,92
K-Nearest Neighbors (KNN)	0,24	0,48	0,88	0,89
Gradient Boosting (GB)	0,07	0,27	0,96	0,96

Table 1: Performance Comparison of Machine Learning Models

As presented in Table 1, the models using Gradient Boosting and Random Forest, combining various models to minimize overfitting, were the most effective ones that caught complex interrelations among the sensor data and RUL compared to other models with smaller MSE and RMSE values and bigger R^2 and CV scores. Especially for the GB model, it showed the best classification performance, with an accuracy of 96.41% based directly on the R^2 score. This is to say that the GB model can explain 96.41% variance in RUL, which is relatively high. Therefore, it scores top among those compared.

The reason why Gradient Boosting performs better than other models is due to the fact that each model is constructed by learning from the mistakes of the previous model and hence provides a better and more accurate decision. While, the Random Forest model derives advantage from the decision trees being random, and hence the resulting aggregation of predictions from several decision trees makes for a much stable and accurate model.

By comparison, the Linear Regression model, which is a comparatively basic linear model, is unable to identify and compute the non-linear relations present in the data correctly, and therefore reads an accuracy of 20. 21%. The Decision Tree and K-Nearest Neighbors models although outperforms the Linear Regression model to some extent but lags behind the ensemble methods due to its high overfitting problems and constraints related to data complexities and overfitting occurring in testing data, giving the accuracies of about 93. 13% and 88. 55%, respectively.

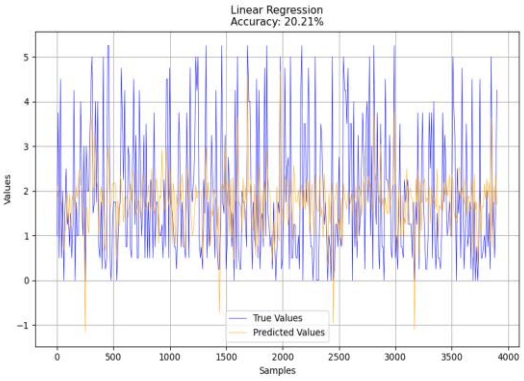

Figure 2: True vs. Predicted RUL values for Linear Regression Model

In figure 2 shows the predicted values of the linear regression model of RUL against the actual values of RUL. From the graph above it is clear that the model’s predictions seriously do not correlate with the actual data and the model itself is linear when it should be depicting non-linearity in the data set.

This observation demonstrates why linear regression is not suitable for this type of prediction problem.

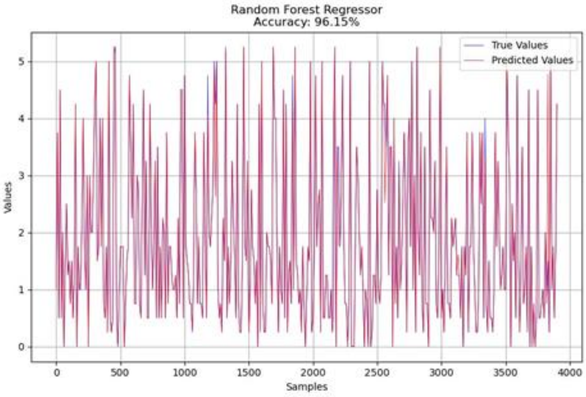

Figure 3: True vs. Predicted RUL values for Random Forest

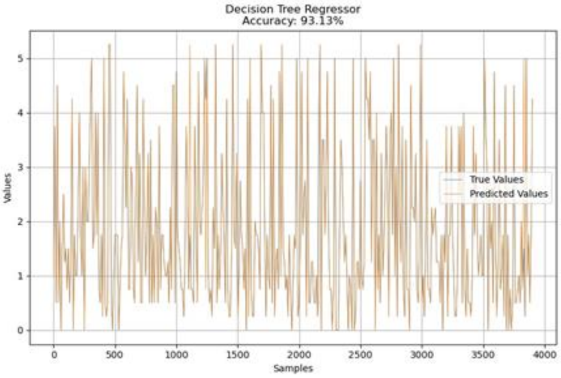

Figure 4: True vs. Predicted RUL values for Decision Tree

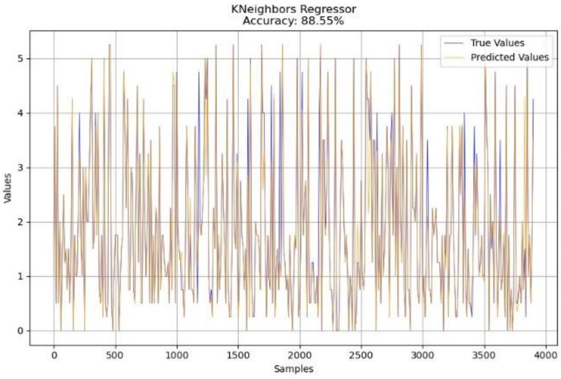

Figure 5: True vs. Predicted RUL values for

K-Nearest Neighbors

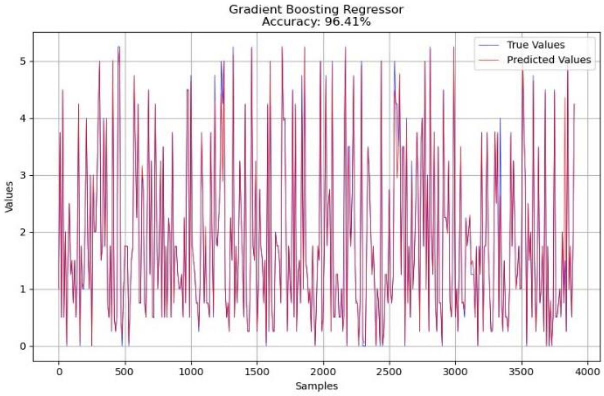

Figure 6: True vs. Predicted RUL values for Gradient Boosting

IV. DISCUSSION

The study indicates that Gradient Boosting as well as Random Forest models produce the best estimation of RUL from the feature obtained from sensors as compared to other models. The Gradient Boosting model performs better because it has the ability to learn from the previous mistakes and the Random Forest model consistently gives accurate results by using a group of decision trees. The simplest Linear Regression model was not sufficient for this data analysis as it could not account for nonlinear correlations. Decision Tree and K-Nearest Neighbors models were also found to have comparatively lower accuracies mainly due to overfitting as well as due to the fact that the data used was complex in nature.

These findings show how Gradient Boosting and Random Forest models can improve the performance of predictive maintenance systems and decrease expenditure due to failure of machines. As for future work, these models should be further validated on the larger and more diverse datasets so as to enhance their effectiveness. Moreover, one should consider applying other advanced prediction methods associated with the ML algorithms, including deep learning algorithms, to improve the percentage of prediction.

V. CONCLUSION AND FUTURE SCOPE

This research effectively illustrates how Graduate Boosting and Random Forest ensemble models can be applied as effective classification models in determining the remaining lifespan of industrial equipment based on real-time sensor readings. When applying these results to practice, the selection of proper models and feature engineering approaches impact the accuracy of RUL predictions significantly. Thus, industries are in a position to improve prognosis of RUL and be capable of scheduling maintenance with decreased downtime, avoiding expensive equip failures and subsequently, leading to improved efficiency and lower costs.

However, despite this success, the study has some limitations. The datasets used, while informative, are limited in size and diversity. Hence, more studies in the future should attempt to test these models with bigger and more diverse databases. Thus, the improvements of machine learning approaches could be attained by applying deep learning algorithms to gain higher classification accuracy and more precise prediction of RUL. Such advanced research can also support various industries in enhancing their maintenance approaches and techniques.

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