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Prediction of remaining useful life and downtime of induction motors with supervised machine learning

Abstract

This research aims to use a vibration monitoring system along with machine learning techniques to predict the downtime and Remaining Useful Life (RUL) of three-phase induction motors in the manufacturing sector. The study obtains measurement data from accelerometer sensors that collect various parameters related to motor performance. The research includes a data preprocessing stage to handle missing data, select predictor attributes, and remove duplicates. Supervised learning algorithms are applied, including Decision Tree (DT), Naive Bayes (NB), Random Forest (RF), and Artificial Neural Network (ANN). The results show that DT and NB models have the best performance in downtime classification, achieving 100% accuracy, recall, precision and F1 values. In terms of predicting Remaining Useful Life (RUL), the RF model outperforms the base model and ANN, showing better results in Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and correlation coefficient.

1. INTRODUCTION

Induction motors are widely used in modern manufacturing, accounting for approximately 40% of electrical energy consumption and representing a critical component of production systems. The most commonly used induction motors are three-phase induction motors, which operate in three-phase power systems and are widely used in various industrial applications due to their large capacity (Sengamalai et al., 2022).These motors operate on the principle of a rotating magnetic field generated by a three-phase electric current flowing through the stator winding. Despite their reputation for durability, induction motors are susceptible to degradation and damage from factors such as mechanical wear, unbalance, and electrical problems. Common types of damage include mechanical imbalance, bearing failure and rotor damage. Therefore, vibration measurement is used as a predictive maintenance approach to check the condition of the motor (Malta et al., 2014).

In the case study conducted at a company in the Fast Moving Consumer Goods sector, the use of 3-phase induction motors as drivers for production machines is of great importance. The reason for evaluating the induction motors is that the number of failures has increased significantly over the past two years. An effective way to detect and predict damage to induction motors is to monitor the vibrations generated during operation. Abnormal vibrations are often an early sign of problems such as misalignment, worn bearings or rotor imbalance. The problem in this case study is that although vibration monitoring has been performed on the motor, damage to the induction motor is difficult to detect, resulting in frequent downtime. This is due to inaccurate analysis of vibration monitoring results by technicians, so a method of automation using machine learning is needed so that vibration monitoring can be analyzed and evaluated with computational support and accurate predictions can be made.

Many studies have shown that machine learning algorithms can be used to classify types of damage and predict the remaining life of machines with an accuracy of more than 90%. Vibration monitoring systems on rotating machinery can be used to diagnose faults and have a positive impact on making more accurate maintenance decisions (Tiboni et al., 2022) . The remaining life of the machine also needs to be predicted to improve the machine life cycle and reduce the failure rate (Wang et al., 2020). Several studies have discussed the use of machine learning in predictive maintenance. A study by Kadyan et al. (2024) analyzed the use of machine learning algorithms including RF, DT, NB, and ANN using IoT (Internet of Things) and achieved high accuracy results. This paper explores supervised learning algorithms to predict downtime and RUL of induction motors using vibration monitoring. The datasets used are also parameters measured under real operating conditions, interpreting the actual conditions obtained from IoT sensors placed on each induction motor. The implementation of this research is a vibration monitoring system that is expected to provide early warning of potential motor failure, enabling more effective and efficient preventive maintenance. Through an application or dashboard system, current conditions can be known and analyzed to determine maintenance or repair activities to be performed. Thus, this research contributes to the development of vibration monitoring systems on induction motors to predict downtime and remaining motor life, can improve predictive activity management and understanding in the implementation of machine learning in the world of industrial manufacturing.

2. LITERATURE REVIEW

Vibration is the oscillatory motion of a mechanical system with respect to its equilibrium position. (Manakova et al., 2019). In the manufacturing industry, vibration is often considered to be an indication of the operating condition of machinery and equipment. Imbalance, component wear, misalignment or resonance are some of the causes of vibration. For maintenance and condition diagnosis of induction motors, vibration measurement is a very important procedure. The purpose of this research is to develop a vibration monitoring system that can identify early fault indicators in the vibration pattern of an induction motor, enabling the prediction of downtime and RUL. RUL is an estimate of the remaining operating time of a piece of equipment before it fails or requires major maintenance. RUL prediction is important in the industrial sector because it can support proactive maintenance planning, reduce unplanned downtime and improve operational efficiency.

According to previous studies by Bienefeld et al. (2022) the following formula is applied to obtain the estimated RUL (RULpred) based on label prediction in regression:

$$RULpred = \frac{t}{ypred} \,.\, (1 - ypred) \tag{1}$$

The mathematical equation above describes how to obtain the RUL prediction, where*(t*) is the current operating time and*(ypred*) is the predicted label at the corresponding time. Using the total time to failure*(T*) and the true label at that time*(ytrue*), the following equation is used to compare the prediction to the actual remaining life (RULtrue).

$$RULtrue = T.(1 - true) \tag{2}$$

RUL prediction methods can be categorized in several ways, including based on the type of algorithm or technique used, or based on the type of data and system knowledge available. (Wang et al., 2020). According to a study by Okoh et al. (2014) the RUL of a component can be determined using various prediction techniques. These approaches fall into the category of techniques and methods. The research conducted explains how to predict the RUL of components using different techniques. The data set was studied using machine learning based methods. The algorithm can make predictions about the data to be evaluated using training and test data. In the study by Li et al. (2019) a combination of regression models and ANN was used to predict the RUL of rolling element bearings. While the ANN model is used to associate vibration characteristics with corresponding damage phases during the natural run-to-failure process of the rolling element bearing, the regression model is used to correct the condition indicators obtained from the bearing vibration signal. In contrast to the regression MSE value of 14.57, the ANN results have an MSE value of 6.78. This figure indicates that ANN is better at predicting the RUL of bearing failures compared to the regression approach. Another study conducted by Tun et al. (2021) investigated a new hybrid technique that combines the RF classifier and SVM(support vector machine) for fault detection and diagnosis in HVAC systems. Although it has fewer sensors and fewer damage symptoms, the proposed hybrid RF-SVM has a high prediction accuracy of 98%. Other machine learning models such as RF, DT, NB, and ANN architectures have been described in various studies. Rzayeva et al. (2023) used DT and SVM models to predict LAN equipment failure. The results obtained by DT have a higher accuracy value of 99.39% compared to SVM's 94.28%. In another paper, Toma et al. (2020) prediction of bearing failures in induction motors using machine learning models. The results obtained by combining Genetic Algorithm with RF give an accuracy value of 99.7%, higher than DT 98% and kNN 97%. Bezerra et al. (2024) Investigate the impact of different feature selection techniques on machine failure prediction using machine learning algorithms. This study evaluates various feature selection techniques, namely Principal Component Analysis (PCA), Minimum Redundancy Maximum Relevance (MRMR), Neighborhood Component Analysis (NCA), and Denoising Autoencoder (DAE), in conjunction with three machine learning classifiers: RF, SVM, and Multilayer Perceptron (MLP). The results show that the integration of PCA with the RF classifier provides optimal performance, achieving an accuracy of 0.98, a precision of 0.97, and a recall of 0.98 in the classification of machine failures. The research of Sekhar et al. (2023) highlight the importance of accurate RUL prediction in improving the reliability of electrified transportation systems, using real-world battery lifecycle data to evaluate machine learning techniques. Machine learning techniques, including RF, DT, and Gradient Boosting Regression, are evaluated for their effectiveness in predicting RUL. The results show that RF has superior accuracy and efficiency, thereby improving sustainable battery management and aligning with the Sustainable Development Goals (SDGs). While another study by Vieira et al. (2024) estimated the RUL of wind turbine main bearings using real-time operational data from a SCADA system. The researchers developed six machine learning regression models (SVR, ISOR, GBR, DTR, ETR, and RFR) to estimate RUL based on data from three turbines with emphasis on temperature variations, wind speed, and net active power. The result demonstrated the effectiveness of the models in estimating RUL while minimizing errors through careful selection and tuning. Prediction of lifetime and RUL of lithium-ion batteries using various modeling techniques, in particular the Particle Swarm Optimization Random Forest (PSO-RF) algorithm to improve search capabilities and avoid local optima, resulting in better prediction accuracy. The model outperforms traditional RF and back-propagation neural network methods, achieving an MAE of less than 2% and an RMSE of less than 3% (Wu et al., 2023).

3. RESEARCH METHODS

3.1. Research framework

This research aims to predict induction motor downtime and RUL through vibration monitoring integrated with IoT technology. Data collected from accelerometer sensors will be analyzed to identify potential motor failures and alert technicians to perform necessary maintenance or repair activities. The application of machine learning in this study will facilitate the analysis and prediction of engine failure and downtime. The supervised machine learning techniques used in this research include DT, NB, RF, and ANN. The first stage in this research methodology is planning. In this stage, the research will begin with a literature review. The second phase is the implementation phase. It starts with finding and collecting the data to be tested. The data used is historical vibration measurement data on induction motors obtained from accelerometer sensors in real time using IoT, so the data uploaded from each sensor to the gateway is downloaded for a period of time for further analysis. The data is then processed by sorting and labeling the data, including time, vibration parameters, downtime events, and the remaining life of the machine until it is replaced or repaired. From the labeled data, supervised learning data training will be performed to obtain predictions for the data to be tested. The Rapidminer software is used for this phase to preprocess and build a machine learning model. Furthermore, the evaluation process of the executed model is carried out to provide an understanding of the research process carried out by testing the performance of the model. The error rate and accuracy of each supervised learning method used is measured using regression and classification matrices. Where for each of these values get a better value than previous research and a good level of accuracy, so that this research will provide maximum output.

In order to implement the model used in this research, it is essential to create a flowchart that provides a comprehensive explanation of the process from the initial raw data to the final model evaluation. Figure 1 illustrates the proposed system implementation flowchart that will be used in this study.

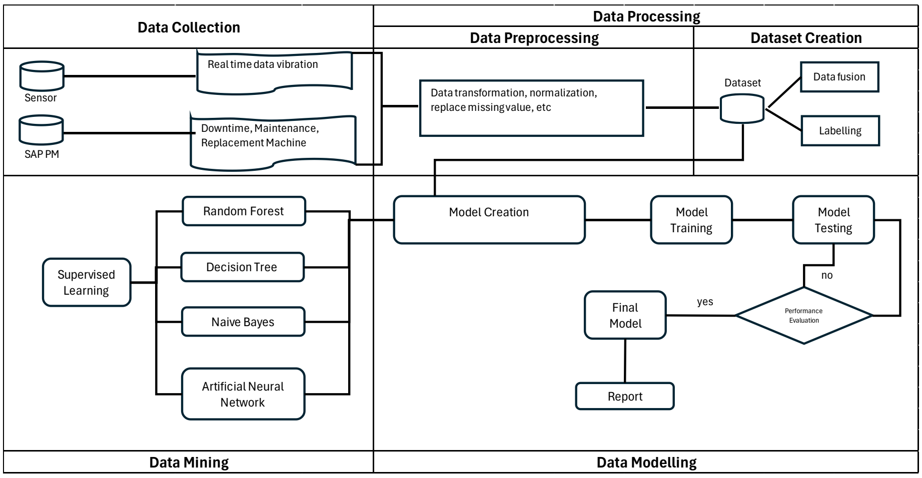

Fig. 1. System implementation flow diagram

3.2. Data collection

To make predictions, a valid data set is required and the patterns can be learned by machine learning. The data used in this research comes from a case study at an FMCG company using vibration monitoring data on 160 Kw induction motors. Vibration parameters are measured using accelerometer sensors located on each induction motor. This data is then transmitted to the cloud so that monitoring data from each motor can be accessed by any user. Figure 2 below illustrates the process of measuring parameters from a three-phase induction motor for monitoring on a dashboard. This visual representation details how data is collected from the motor, transmitted through the IoT system, and displayed in a user-friendly format for real-time analysis and decision making.

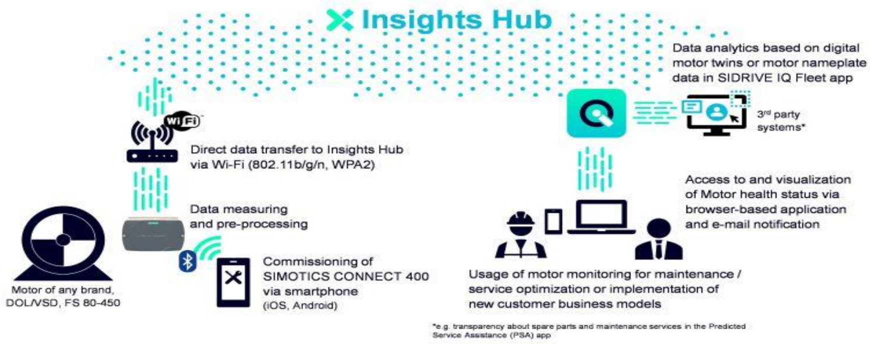

Fig. 2. IoT dmart densor architecture (Siemens Insights Hub)

3.3. Data pre-processing

To analyze downtime and RUL for maintenance and repair of induction motors, historical data is extracted from the SAP Plant Maintenance module, which records all maintenance and repair activities. This data is combined with vibration parameters from accelerometer sensors. The goal is to process this data using machine learning techniques to develop a predictive model that can help technicians analyze downtime and RUL. The dataset undergoes preprocessing, which includes selecting the data for labels and attributes, selecting the relevant features, normalizing the data to bring it into a more manageable range, adding data to address missing values, removing duplicates, and dividing the data for testing and training, 90% for training and 10% for the test set.

3.4. Proposed model

This study will use a number of supervised learning techniques. Each technique uses a different process to construct a model that will be applied to test and training data. Each approach, which has been used in previous studies and will serve as a baseline or reference point for building models for this research, is described in this subchapter.

3.4.1. Downtime classification

Decision Tree is one of the supervised learning methods commonly used to classify target labels with easy-to-understand result interpretation in the form of a decision tree. Previous research by Hartanta et al. (2023) using DT and cross-validation to predict the assessment grade of final year students with modeling performance results that have an accuracy of 99.24%. In this research, the DT parameters will become the base model to be studied using the pneumatic fan motor vibration measurement data set. The following decision tree parameters are used.

Tab. 1. Decision Tree parameter

Hyperparameter	Base value
Maximal Depth	10
Confidence	0,1
Minimal Gain	0,01
Minimal Leaf Size	2
Minimal Size for Split	4
Number of Prepruning Alternatives	3

For comparison, Naive Bayes is explored to classify downtime on induction motors instead of Decision Tree. This model uses the probability of occurrence method between classes or attributes in a target label. He et al. (2021) investigate a fault diagnosis method for photovoltaic (PV) systems using a Fine-Tuning Naive Bayes (FTNB) model, which achieves 98.59% accuracy with ideal data and 97.32% accuracy with noisy data. The FTNB model adjusts probability estimates based on the probability of classification errors and uses existing maximum power point and meteorological data to diagnose various fault types, including open circuit, short circuit, partial shading, and abnormal degradation. The refined Naive Bayes model uses this parameter for the base model below.

Tab. 2. Naïve Bayes parameter

Hyperparameter	Base value
α	2
β	2
η	0,01

The parameters of the base model mentioned above serve as a basis for modeling, with the goal of improving the performance evaluation to achieve the optimal proposed model.

3.4.2. RUL prediction

Previous classification model for downtime label target shows an indication of failure in the induction motor, this research also conducted a study to predict the remaining life of the induction motor. The RUL of each induction motor is obtained from historical machine damage data when the motor fails. When the induction motor is operating under normal conditions, the RUL of the motor is the number of hours the motor runs from startup to shutdown or retirement. This RUL is used to determine the remaining life of the motor that will experience failure or downtime according to the downtime classification modeling described in the previous subchapter, so that operators or technicians can take proactive steps to plan corrective actions before the induction motor fails completely, which can result in a fatal shutdown of the production line. The models that will be performed to predict the RUL of the pneumatic fan induction motor are Random Forest and Artificial Neural Network.

Random Forest is a supervised learning method that combines several methods at once, or ensemble learning, which is a collection of many decision trees. Research conducted by Antgren & Lindberg Brännström (2022) in predicting the downtime of battery production machines, random forest has the best performance. The most optimal hyperparameters in the study are applied in this study, with the following parameters.

Tab. 3. Random forest parameter

Hyperparameter	Base Value
Max_depth	15
Max_features	sqrt
Min_samples_leaf	1
Min_samples_split	2
n_estimators	750

The n_estimators parameter or number of decision trees is analyzed for several values including 100, 500, 750, 1000 and 1500 to determine the effect of these changes, with a default maximum depth value of 15. To analyze other parameters that contribute to modeling, an adjustment is also made to the Maximum Depth parameter or Decision Tree Depth, which determines the number of nodes or branches in a tree. Several values are examined for changes in the maximum depth parameter with values of 5, 10, 15, and 20 as well as a value of 100 to determine if there is a drastic change in the effect of increasing the parameter on modeling performance.

The second model used to predict RUL is an artificial neural network. This model mimics the human brain network in making good modeling by following a system of interconnected neurons to process and analyze data. (Geetha & Nasira, 2014) In his research proposed the application of neural networks for weather forecasting has good accuracy. From this research, the neural network parameters that will be applied in this research include

Tab. 4. Neural network base model

Hyperparameter	Base value
Training Cycles	1000
Learning rate	0,3
Momentum	0,2

This model is run with several changes to the training cycles, learning rate, and dynamics.

3.5. Evaluation Methods

The evaluation process is necessary to determine the performance and accuracy of the supervised learning methods and models used. Evaluating the performance of machine learning models is an important step in assessing how well the model works and whether it can be relied upon to make predictions or decisions based on new data. In this research, downtime prediction is done using the classification method and RUL prediction is done using the regression method, so each model performance evaluation has different evaluation metrics. The following are some of the metrics that will be used to evaluate the performance of machine learning models.

1. Prediction RUL model
   a. RMSE (Root Mean Square Error)

Root Mean Squared Error (RMSE) is one of the most commonly used metrics to measure the performance of machine learning models, especially in regression problems. RMSE measures the average error between the value predicted by the model and the true value. This value gives an idea of how close the model's prediction is to the true value (Shanmugavalli & Ignatia, 2023). The following is the formalization of the RMSE.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(yi - \widehat{yi})^2} \quad (3)$$

   b. MAE (Mean Absolute Error)

MAE is a method of measuring the average absolute error between the predicted value and the actual value, MAE gives an idea of how large the average deviation is between the model prediction and the actual value (Fadilah et al., 2020). The MAE formula is defined as

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|yi - \hat{yi}| \quad (4)$$

c. MAPE (Mean Absolute Percentage Error)

MAPE measures the average percentage error between the actual value and the predicted value (Shanmugavalli & Ignatia, 2023).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{yi-\widehat{yi}}{yi}\right| x\ 100 \tag{5}$$

d. R Square (R^2) or Correlation

The R^2 error is a metric that indicates how well the predictive model explains the variability in the data. This matrix takes values between 0 and 1, with values closer to 1 indicating a better model (Shanmugavalli & Ignatia, 2023).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(yi-\widehat{yi})^2}{\sum_{i=1}^{n}(yi-\widehat{y})^2} \tag{6}$$

2. Classification downtime model

a. Accuracy

Accuracy is a metric used to measure how well a classification model predicts correctly over the entire data set. The accuracy formula takes into account the sum of true positives (TP) and true negatives (TN) in the numerator, and the sum of all entries in the confusion matrix, including false positives (FP) and false negatives (FN), in the denominator (Grandini et al., 2020).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{7}$$

b. Precision

Precision is a metric used to evaluate the performance of a classification model by measuring the proportion of units predicted to be positive by the model that are actually positive. Precision provides an indication of how "good" or how little "error" the model makes in making positive predictions (Grandini et al., 2020).

$$Precision = \frac{TP}{TP+FP} \tag{8}$$

c. Recall

Recall is a metric used to measure the model's prediction accuracy for positive classes. Recall gives an idea of the model's ability to "remember" or recognize positive data in its entirety (Grandini et al., 2020).

$$Recall = \frac{TP}{TP+FN} \tag{9}$$

d. F1-Score

F1-Score is a metric used to evaluate the performance of classification models by combining Precision and Recall in the form of a harmonic mean. F1-Score reaches its best value at 1 and its worst value at 0, with equal contributions from Precision and Recall (Grandini et al., 2020).

$$F1 - Score = 2\,.\left(\frac{precision\,.\,recall}{precision+recall}\right) \tag{10}$$

There will be different performance rating matrices for each model used to classify downtime and predict RUL. The final model method should be able to correctly predict downtime and RUL with high accuracy and low error values. This can help make the right predictive maintenance decisions and reduce maintenance costs.

4. RESULT AND DISCUSSION

4.1. Preprocessing stage

Data preprocessing plays a critical role in ensuring the accuracy and reliability of predictive models. The preprocessing phase involves several key steps, including data cleaning, normalization, and feature selection.

First, the raw data collected from IoT sensors is examined to identify and correct any inconsistencies or missing values that could affect model performance. Listed below are the missing values contained in the dataset.

Tab. 5. Missing values

Attribute	Missing values
Acceleration Geometric Mean	1701
Bearing State	1701
Unbalance State	1701
Velocity Geometric Mean	1701
Misalignment State	1626

Replacing missing values is a critical step in data preprocessing, especially in the context of machine learning and statistical analysis. Missing data can come from a variety of sources, including sensor malfunctions, data entry errors, or system outages. If not addressed, these gaps can lead to biased results, reduced model accuracy, and invalid conclusions. For numerical data, missing values can be replaced with the mean of the data.

Normalization techniques are then applied to standardize the data and ensure that all features contribute equally to the analysis. Feature selection is then performed to identify the most relevant parameters that influence RUL and downtime predictions, thereby reducing dimensionality and increasing computational efficiency. By carefully preprocessing the data, the study aims to improve the robustness of the machine learning algorithms employed, ultimately leading to more accurate predictions and better maintenance strategies for induction motors.

4.2. Machine learning model for downtime classification

Downtime is the target label categorized in this study. On the other hand, a label has two categories: YES, which indicates a failure of the pneumatic fan's induction motor, and NO, which indicates no failure or that the induction motor is working well. The NO label category has more entries in the data set than the YES label category, where there are 14806 data points for the NO label and only 22 data points for the YES label.

Tab. 6. Downtime label

Label	Count of label	Fraction
NO	14806	0.999
YES	22	0.001

To deal with unbalanced data, characteristics are required according to the statistical description of the table. The SMOTE approach is one of the most widely used data resampling methods. The Synthetic Minority Over Sampling Technique, or SMOTE, resamples minority data by generating sample data depending on the number of nearest neighbors from the data centroid or nearest neighbor. It is expected that this approach will be able to correct imbalanced data. In addition to these methods, a down-sampling strategy will be used in this study, in which the majority of the data will be randomly selected. A comparison of these two data sampling techniques will be discussed in the next subchapter. The modeling used to classify downtime as a target uses 2 supervised models, Decision Tree and Naive Bayes.

In addition to the basic parameters in the Decision Tree model, the resampling technique used by SMOTE also uses the default value for nearest neighbors with a total of 5. Below is a comparison of the amount of data resampled by SMOTE.

Tab. 7. Comparison after SMOTE

Label	Count of label	Fraction
NO	14806	0.500
YES	14806	0.500

From Table 7, the SMOTE technique increases the YES class label from 22 to 14806, this can be done by the mechanism of SMOTE which works by identifying minority class instances, finding K-Nearest Neighbors (defined k=5), randomly selecting a neighbor then generating a synthetic sample. This effectively creates new data points that are similar to existing minority samples. For the down samples, the number of NO downtime labels, which was previously 14806 data points, was randomly reduced to 100 data points. With the parameters used above, the performance evaluation of the decision tree model used yields the following performance results.

Tab. 8. Decision Tree performance

Methode	Accuracy	Precision	Recall	F1-Score
DT base model	99,97	99,98	87,50	93,32
DT Down Sample	96,72	98,08	90,91	94,36
DT SMOTE	100	100	100	100

For the base model, the resulting performance has a fairly good accuracy level, but has a low recall value. With the down-sampling technique, the performance of the resulting model has lower accuracy, precision, recall and F1 scores compared to using the SMOTE technique. To see the interpretation of the decision tree generated using these two techniques, it is shown in the following figure. Where the use of AdaBoost is used as a combination in the use of modeling algorithms to improve model performance.

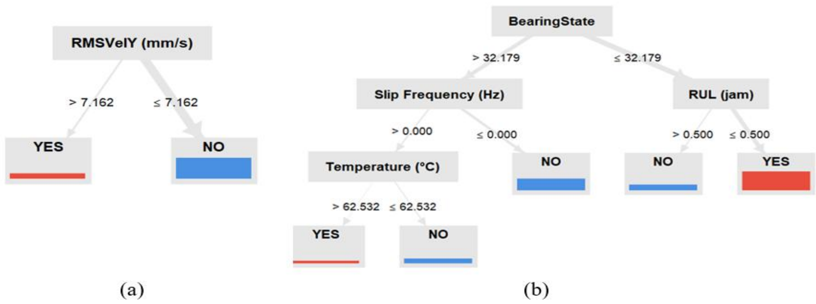

Fig. 3. Comparison between downsample tree (a) and SMOTE tree (b)

From Figure 3, there is a notable difference between the decision trees generated by the downsampling technique and the SMOTE. In the case of downsampling, the downtime classification decision is based solely on a single attribute, RMSVelY. Specifically, if the value of this attribute exceeds 7.162, it is classified as indicative of downtime. Conversely, the decision tree generated by SMOTE includes four attributes. The classification begins with the bearing condition, where a value less than or equal to 32.179, combined with a RUL less than or equal to 0.500, indicates the occurrence of downtime. In another branch of the tree, if the bearing condition is greater than 32.179, along with a slip frequency greater than 0 and a temperature greater than 62.532, the classification also indicates downtime. This analysis highlights the differences in the complexity and number of attributes used in the decision making process for downtime classification between the two techniques, suggesting that SMOTE may provide a more nuanced understanding of the factors contributing to downtime events.

The second model used to classify induction motor downtime is Naive Bayes. This model uses the probability of occurrence method between classes or attributes in a target label. Resampling techniques are also used in this modeling, using down-sampling and SMOTE techniques, with the same parameters as in the previous modeling, where the number of samples for each label class is 100 for down-sampling and the nearest neighbor is 5 for SMOTE. The performance of the resulting Naive Bayes model has the following values of accuracy, precision, recall and F1 score.

Tab. 9. Performance evaluation of Naïve Bayes

Methode	Accuracy	Precision	Recall	F1-Score
NB base model	99,97	99,98	87,50	93,32
NB Down Sample	98,36	99,02	95,45	97,20
NB SMOTE	100	100	100	100

The SMOTE technique has higher accuracy, precision, recall and F1 score values compared to the down-sample and base model techniques. The table below summarizes the comparison between the base model and the proposed model of DT and NB.

Tab. 10. Downtime classification model

Model	Accuracy	Precision	Recall	F1-Score
DT base model	99,97	99,98	87,5	93,32
NB base model	99,97	99,98	87,5	93,32
DT Down Sample	96,72	98,08	90,91	94,36
NB Down Sample	98,36	99,02	95,45	97,2
DT SMOTE	100	100	100	100
NB SMOTE	100	100	100	100

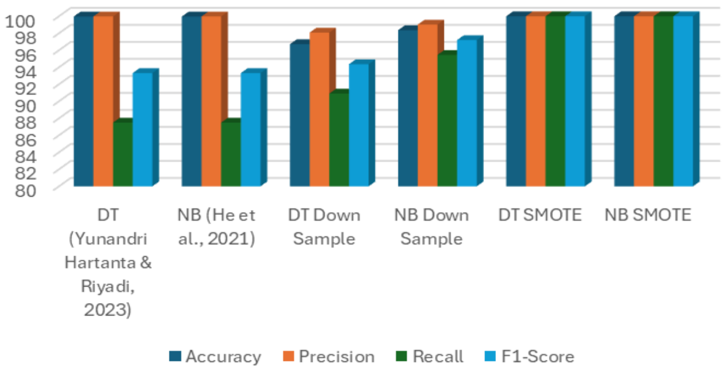

Fig. 4. Downtime classification model

4.3. Machine learning model for RUL prediction

The Remaining Useful Life (RUL) prediction models used in this study are Random Forest and Artificial Neural Networks (ANN). The baseline models serve as initial references for implementing improvements in the proposed models, resulting in the following performance results. This approach underscores the importance of establishing a baseline performance benchmark that facilitates the identification of enhancements and optimizations in the subsequent model development process.

Tab. 11. Base model performance

Performance	RF (Antgren & Lindberg Brännström, 2022)	ANN (Geetha & Nasira, 2014)
RMSE	45,642	115,713
MAE	26,335	98,681
MAPE	18,67	55,25
Correlation	0,945	0,762

Based on the baseline model adopted from previous studies, this research aims to develop an improved model by analyzing the variations in the parameters for each respective model. As detailed in the research methodology chapter, the proposed Random Forest model will explore changes in the parameters of n_estimators and maximum depth. This analytical approach is intended to optimize the performance of the model by systematically adjusting these critical parameters. The n_estimators parameter, or number of decision trees, is analyzed for several values including 100, 500, 750, 1000 and 1500 to determine the effect of these changes, with a default maximum depth value of 15. The table below shows the results of modeling performance for the adjusted parameters.

Tab. 12. Performance of random forest with adjusted n_estimator

Performance	100	500	750	1000	1500
RMSE	48,096	45,664	45,857	45,761	45,642
MAE	28,6	26,453	26,641	24,487	26,335
MAPE	20,41	18,73	18,88	18,77	18,67
Correlation	0,943	0,945	0,945	0,945	0,945

From the performance generated above against several performance evaluation matrices at different numbers of decision trees, the changes in the adjusted parameters are not very significant even though the parameters have been increased. However, the table above shows that as the number of decision trees increases, the error value decreases and the correlation between the predicted value and the true value becomes closer to 1.

To analyze other parameters that contribute to the modeling, an adjustment is also made to the maximum depth parameter, or the depth of the decision tree, which determines the number of nodes or branches in a tree. Several values are examined for changes in the maximum depth parameter with values of 5, 10, 15, and 20 as well as a value of 100 to determine if there is a drastic change in the effect of increasing the parameter on modeling performance. The table below shows the results of modeling performance for the adjusted parameters.

Tab. 13. Performance of random forest with adjusted maximal depth

Performance	5	10	15	20	100
RMSE	92,677	54,335	45,642	44,511	44,424
MAE	64,214	34,203	26,335	25,217	25,123
MAPE	44,66	23,99	18,67	17,99	17,93
Correlation	0,758	0,924	0,945	0,948	0,948

From the performance generated above on several performance evaluation matrices at various numbers of different tree depths, changes in the adjusted parameters significantly affect the model performance results. The larger the maximum depth value, the smaller the error produced, with the correlation between predicted and actual values approaching 1. A comparison is also made with the use of pre-pruning with n_estimator 100 and depth 100. Where this pre-pruning acts as a pruning of the decision tree to speed up the computation time and prevent over-fitting. The following comparison results are obtained. The following graph visualization shows the RUL prediction and the actual value with the best model performance.

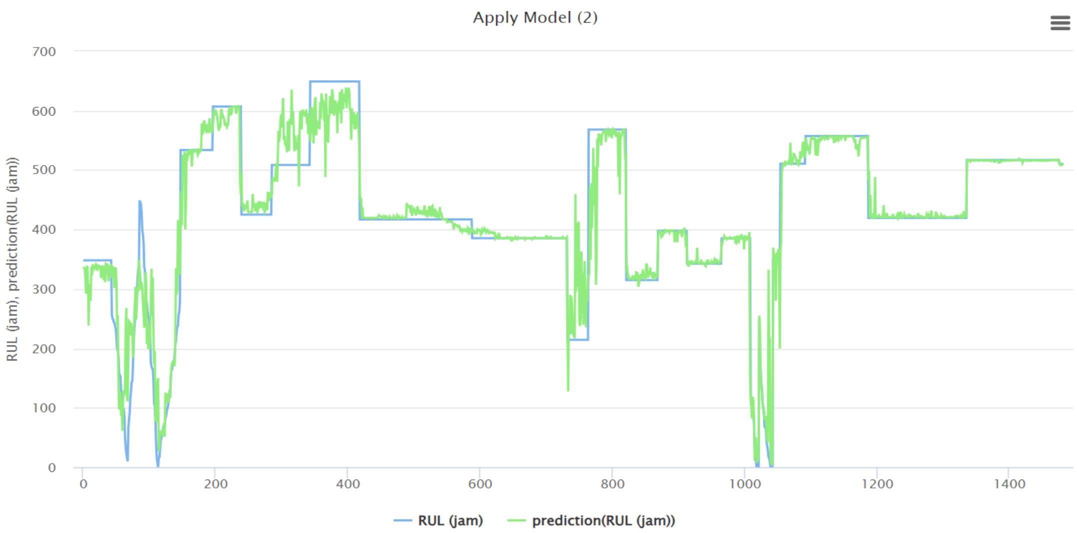

Fig. 5. Comparison of proposed model RF

The graph shows the number of data points for each RUL value. The X-axis represents the number of data points, and the Y-axis represents the RUL value. The blue line represents the actual RUL value, and the green line represents the predicted RUL value. As seen at figure 5 above, it is evident that the predicted values of RUL closely align with the actual RUL values when utilizing the best model with various tuning parameters was found to produce the smallest error value with the following parameters: n_estimator = 1500, max_depth = 100, and no pre-pruning, resulting in a correlation coefficient of 0.952 and a percentage error of 13.56%. Subsequently, this proposed Random Forest model is compared with other, which is ANN. The performance metrics of the baseline ANN model are presented in table 12, where the performance of the resulting model is still not optimal, so parameter tuning is carried out with several changes to the training cycles, learning rate, and momentum. The following are the results of several parameter adjustments.

Tab. 14. Neural network with adjusted training cycles

Performance	100	1000	2000
RMSE	118,19	115,713	116,087
MAE	100,155	98,681	98,882
MAPE	55,46	55,25	55,52
Correlation	0,75	0,762	0,764

Tab. 15. Neural network with adjusted learning rate

Performance	0,01	0,3	0,9
RMSE	87,678	118,19	191,467
MAE	63,946	100,155	162,927
MAPE	39,22	55,46	92,09
Correlation	0,73	0,75	0,543

Tab. 16. Neural network with adjusted momentum

Performance	0,01	0,2	0,9
RMSE	87,96	87,678	83,437
MAE	64,203	63,946	58,538
MAPE	39,51	39,22	38,49
Correlation	0,728	0,73	0,773

Changing the training cycle parameter does not have a significant impact on modeling performance. However, the changes are not linear in some performance metrics such as RMSE and Correlation. Where increasing the number of training cycles actually makes the error value in the RMSE and Correlation metrics worse. For the learning rate change, the smaller the value, the better the resulting error, which means the prediction is close to the true value. In addition, the change in momentum actually has a linear change, where the larger the momentum value, the better the model performance. From several parameter tuning trials, optimal results were obtained with the following parameter values.

Tab. 17. Optimum parameter neural network

Parameter	Optimum Value7,5
Training Cycles	1000
Learning rate	0,01
Momentum	0,9

The resulting neural network architecture model is shown below.

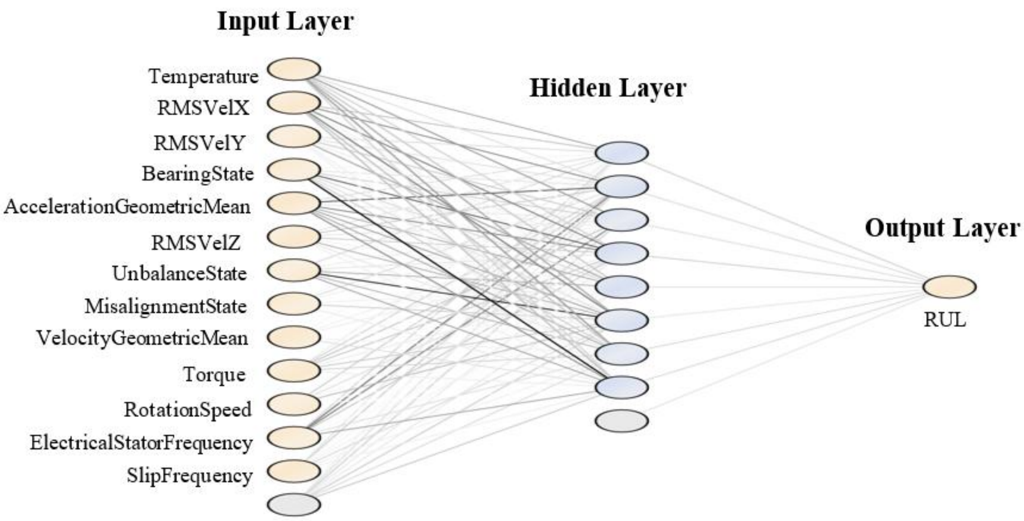

Fig. 6. Neural network architecture

Tab. 18. Optimum neural network performance

Performance	Value
RMSE	75,915
MAE	53,404
MAPE	32,58
Correlation	0,809

Figure 6 shows that the neural network architecture generated from this model uses an input layer with 13 parameters, a hidden layer with eight neurons, and an output label representing the RUL value of the motor. The graph below compares the RUL prediction with the actual value, as shown by the modeling performance results.

Fig. 7. Optimum neural network performance

From the results of the plot comparing the predicted RUL with the actual RUL generated by the proposed ANN model in this study, it is evident that the predicted RUL values are not as accurate as those generated by the proposed RF model. This observation suggests that the ANN model may require further refinement or optimization to improve its predictive performance. The following table summarizes the comparison between the base model and the proposed model from RF and ANN.

Tab. 19. RUL prediction model

Model	RMSE	MAE	MAPE	Correlation
RF	45,642	26,335	18,67	0,945
ANN	115,713	98,681	55,25	0,762
Improve RF	40,531	19,417	13,56	0,952
Improve ANN	75,915	53,404	32,58	0,809

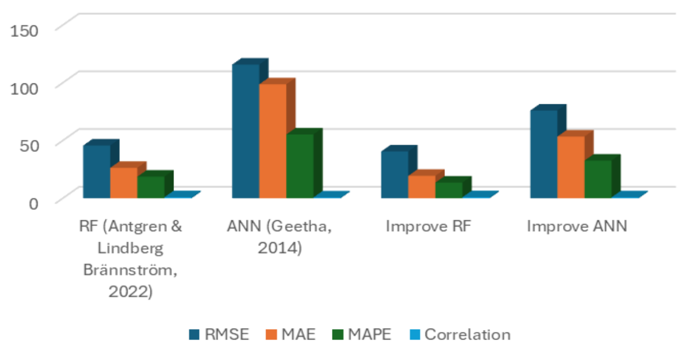

Fig. 8. RUL prediction model

4.4. Vibration monitoring system

In the era of automated industries, machine learning technology is widely used. The most common application is predictive maintenance, which uses ML to predict machine failures before they occur and minimize damage. The best models in previous modeling are the Decision Tree and Random Forest models. Based on these results, the RapidMiner extension file is transformed into Python format to create a webpage that allows technicians to view downtime and RUL predictions based on the parameters entered. This webpage creates a dashboard that displays intuitive visualizations of important vibration parameters, making it easier for personnel to interpret and analyze machine conditions.

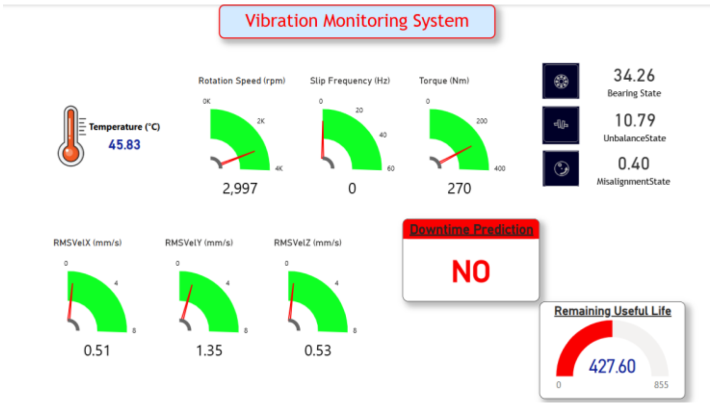

Fig. 9. Visualization of vibration monitoring system

The visualization shown in Figure 9 consists of several measurement parameters derived from smart sensors located on each monitored induction motor. The downtime and RUL labels predicted by the best ML model in this study are obtained from the web page previously described, so that the condition of the motor can be observed using a combination of this web page and the vibration monitoring dashboard. This vibration monitoring system is expected to be a tool for reducing unpredictable engine failures, increasing planned maintenance activities, and reducing the costs incurred due to the damage that occurs.

5. CONCLUSION

Case studies at PT XYZ show that predicting damage to induction motors is challenging because technicians and operators have a poor understanding of damage indicators. Vibration sensors combined with IoT enable instantaneous detection of changes in the condition of induction motors. The results of machine learning models for predicting motor downtime and RUL can serve as a reference for identifying problems and enabling timely preventive maintenance activities. The Decision Tree and Naive Bayes models show exceptional effectiveness in classifying downtime events. The SMOTE resampling approach can effectively address the challenges associated with inhomogeneous downtime data. The integration of AdaBoost with Random Forest and Naive Bayes with SMOTE yields an optimal performance matrix with accuracy, precision, recall and F1 scores of 100%. The frequency of downtime is classified and the RUL of induction motors is estimated using Random Forest and Neural Network models. The optimal performance was achieved with Random Forest after numerous parameter tunings. This study can be applied to similar fields for managing induction motor failures through the integration of IoT sensors and machine learning models. In future studies, the modeling performance of RUL estimation needs to be improved to ensure that the estimated lifetime of the induction motor closely matches the real-world conditions. Integration of the resulting model with IoT is essential for real-time monitoring of a dashboard that displays damage indicators and remaining motor life.

Data Availability

Dataset is available from the Zenodo Repository, DOI: 10.5281/zenodo.15637023

Author Contributions

Muhammad Dzulfiqar Anindhito: Conceptualization, Methodology, Software, Data curation, Writing-Original draft preparation, Visualization, Software, Validation. Suharjito: Supervision, Reviewing. All author agreed with final manuscript.

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