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Machine Learning-Enabled Predictive Maintenance of Electric Motors

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ABSTRACT

As industries increasingly depend on electric motors for critical operations, ensuring their reliability and efficiency is essential. This paper presents a comprehensive analysis of data-driven approach for predictive maintenance aimed at optimizing system performance and minimize unplanned downtime. Leveraging advanced machine learning algorithms using Python programming language, the proposed method integrates data from electric motors—including temperature, vibration, and current to develop predictive models. Using Python to implement predictive maintenance for electric motors entails a methodical process that includes data collection, preprocessing, model development, and real-time monitoring. By training these models on historical data, the framework was able to detect miniature changes in motor behaviour that indicate potential issues. Results from the study show a range of output fault variations produced by all trained models. These miniature variations highlight how accurate the data-trained models are at predicting faults. By adopting data-driven methodologies, industries can enhance resource allocation, streamline maintenance operations, and extend the lifespan and efficiency of electric motor systems.

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1. Introduction

Innovations in industry technologies enhance industrial production to satisfy the demands of intelligent manufacturing systems. Although, electric motors are the backbone of many industries, they are rarely given much industrial attention. Electric motors are essential to almost every facet of contemporary industries (Emadi, 2018). Similar to other rotating machinery, motors can break down, wear out, or degrade over time. A motor will eventually fail if nothing is done during the deteriorating process, which causes the operating environment and conditions to worsen. If one or more busy motors fail, there could be a loss of capacity and very high repair and maintenance expenses (Aniket et al., 2021).

Reactive, preventive, and predictive maintenance (PdM) are among the various forms of electric motor (machine) maintenance that have been developed and put into practice (Noor et al., 2023).

Reactive maintenance is applied when a motor breaks down. While preventive and predictive maintenance can be carried out during regular motor operation (Zhang et al., 2019). Preventive maintenance, however, is more expensive and results in less motor uptime because it necessitates shutting down of the motor and must be performed on a scheduled basis. In addition, the motor's health profile is non existing, because there was no continuous

monitoring of the motor's condition (Tao et al., 2018).

Predictive maintenance, promises increased reliability and longer equipment life (Mustafa et al., 2021). Predictive maintenance's primary goal is to identify problems before they arise in order to maximize equipment lifespan and avoid unplanned motor downtime.
Predictive maintenance employs a number of mathematical techniques, such as machine learning, reliability analysis, statistical process control (SPC), time series analysis, and failure modes and effects analysis (FMEA) (Achouch et al., 2023). By utilizing sizable datasets, machine learning (ML) algorithms are especially well-suited for fault detection.

Sutharssan et al. (2015) and Ran et al. (2019), examined machine learning as one of the several PdM strategies, which they classified into model-driven, hybrid, and data-driven methods. The data-driven methods were divided into statistical and machine learning approaches. Carvalho et al. (2019) and Theissler et al. (2021), evaluated machine learning for predictive maintenance in general and evaluated the effectiveness of cutting-edge techniques in relation to the significance of data-driven approaches.

Predictive maintenance relies heavily on high quality and sufficient data. However, data collection and processing can be time-consuming and data quality issues can arise from sensor inaccuracies, as shown in previous researches.
Complementary to these studies, this work focuses on machine learning-based predictive maintenance (PdM) for electric motor models. It does this by using the motor's generated data to find potential warning indications that could indicate a failure or downtime in an electric motor. The promising target is fault detection of electric motor by utilizing past maintenance data and/or system health state information of the motor. It attempts to guarantee a prompt repair prior to a failure while simultaneously attempting to prevent an untimely and expensive system repair.

Random Forest, Linear Regression, Naïve Bayes and Support Vector Machine (SVM) machine learning algorithms are engaged in this study using data from a functional alternating current (AC) motor system. The main goal is to apply these set of classification algorithms to obtain a classification model for faults classification and embed the model in python application to predict electric faults in motors earlier before they occur.

2. Materials and Methods

The methodology involves carrying out multiple experiments on datasets utilizing the Random Forest, Linear Regression, Naïve Bayes, and SVM algorithms (Pranckevicius & Marcinkevičius, 2017). To achieve the best accuracy and precision, experiments are run on each algorithm separately as well as in combinations.

When these algorithms are combined, averaged, and compared, they all produce results that are as reliable and accurate as possible. Several algorithms are run through the dataset in order to identify errors. To determine the outcome, the accuracy of the data gathered from each of them is examined.

The collection of datasets is the first step (the faulty dataset is used for the model as shown (Table 1), followed by preprocessing and the application of the Natural Language Toolkit for the features extraction method.

Table 1: Fault parameters to detect.

Parameters	Fault type
Current	1
Voltage	0
Temperature	1
Humidity	0
Vibration	1

After splitting the dataset, next is to apply machine learning algorithms, and build the suggested classifier model. Following the application of Naïve Bayes, Random Forest, Binomial Linear Regression, and SVM to the system response, a model containing the response message is generated. After testing is completed on a test dataset and the results are confirmed, the precision must be observed to ensure acceptance. The predictive fault classification system operates as shown in Figures 1 and 2.

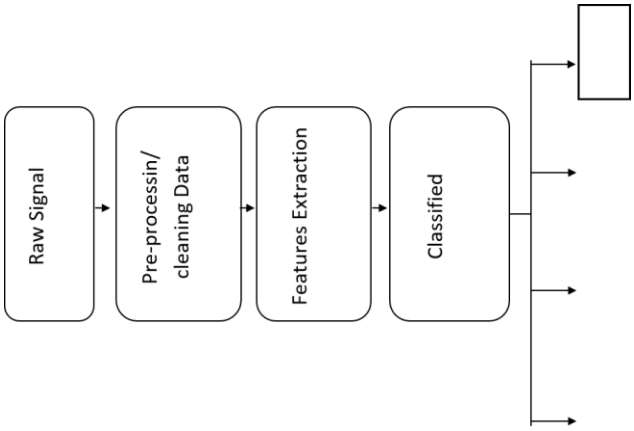


Figure 1: The workflow of the system

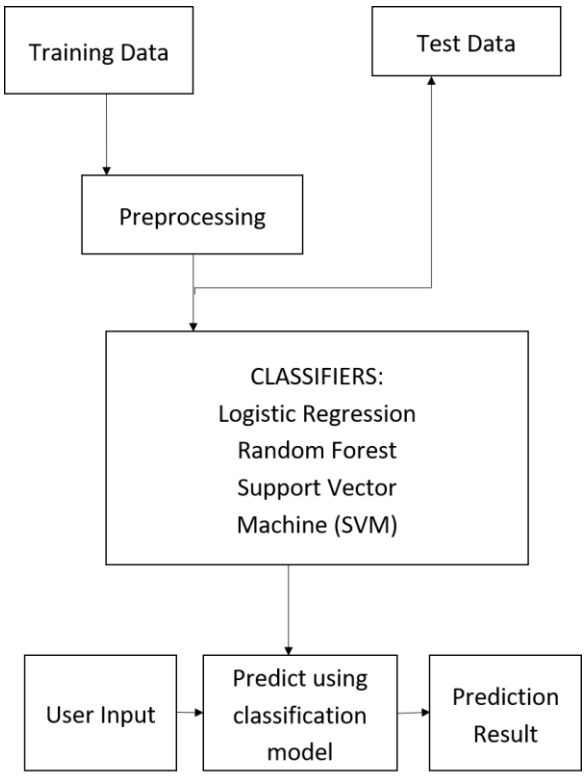


Figure 2: Model of proposed system

2.1 Processing and Training the Datasets

Following the creation of the datasets, the data was processed. To do this, the file was read from its directory using the pandas function. All necessary processing packages, including tensor flow, sklearn model selection, and sklearn processing, were included. The processing steps involved importing the necessary processing packages, loading the data file, and separating the feature and target variable. The steps include:

i. Encoding the target variable.
ii. Scale the features to a specific range.
iii. Split the data into training and testing
iv. Define the neural network architecture.
v. Compile the model.
vi. Train model
vii. Save the trained model.

2.2 Prediction with the Trained Model

Following processing, a new set of fault data was added to the model so that it could predict faults using the trained model file (Figure 3).

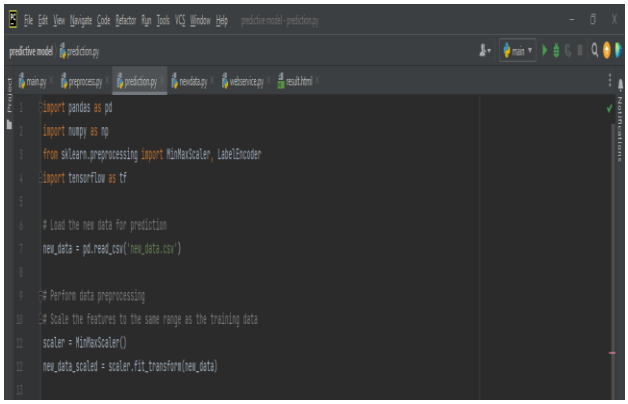


Figure 3: Script for the Trained Model

The new data file was first read and processed to make it appropriate for the prediction model, after which all necessary modules were included. Following that, the new data was sent for prediction, the trained model was loaded, and the various faults were defined. Eventually, the newly created fault data file was read, examined, and fed into the prediction model. The outcomes were then displayed in the run terminal.

3. Results and Discussion

The presented results show a range of outputs produced by all trained models from the first to the fifth iteration. These minute variations highlight how accurate the data-trained models are at predicting faults. Furthermore, the heat map plot (Figure 4), effectively displays the most common issues that the motor under consideration has, as determined by the dataset.

The design performance was evaluated through a series of tests, and the trained model was created by training on a range of data sizes. Once acquired, the model's prediction accuracy was noted. The newly created model was applied to a new set of data, and the results were plotted (Figure 4).

Table 2 and Figure 5 illustrate that in comparison to other faults, trained model 1 was able to determine that the current was at its highest level (1.000 pu). Trained model 2, established that the voltage was at its highest level (1.000 pu). The sample's outcome for trained model 3, revealed several fault occurrences that indicate the electric model's temperature is at the highest level (1.000 pu). Meanwhile, the result obtained from trained model 4, showed the different fault occurrence indicating the intensity of humidity (1.000 pu) in the electric model. Also, trained model 5, shows the different fault occurrence indicating the intensity of vibration (1.000 pu) in the electric model.

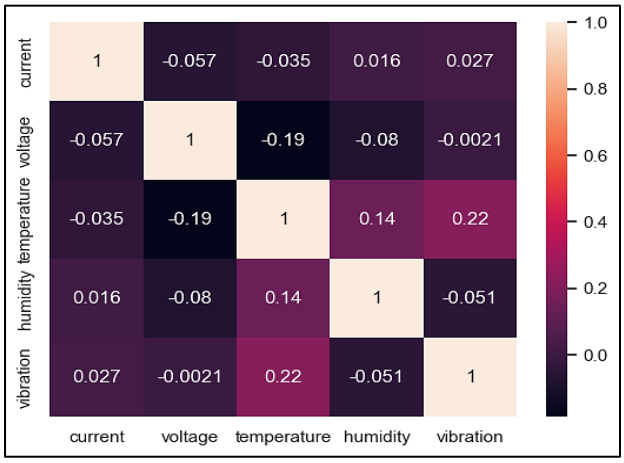


Figure 4: Heat map showing the outcomes for the five model samples.

Upgrading the model's performance further has the potential to improve its performance, an approach that can be practically applied to a real-world motor. Using Python to implement predictive maintenance for electric motors entails a methodical process that includes data collection, preprocessing, model development, and real-time monitoring. Because of its extensive library ecosystem, Python is an effective tool for all phases of the predictive maintenance process.

Table 2: Results of Fault Occurrence Values for the Trained Models

Trained Model	Current (pu)	Voltage (pu)	Temperature (pu)	Humidity (pu)	Vibration (pu)
1	1.0000	0.0570	0.0350	0.0160	0.0270
2	0.0570	1.0000	0.0190	0.0800	0.0021
3	0.0350	0.1900	1.0000	0.1400	0.2200
4	0.01600	0.0800	0.1400	1.0000	0.0510
5	0.0270	0.0021	0.2200	0.0510	1.0000

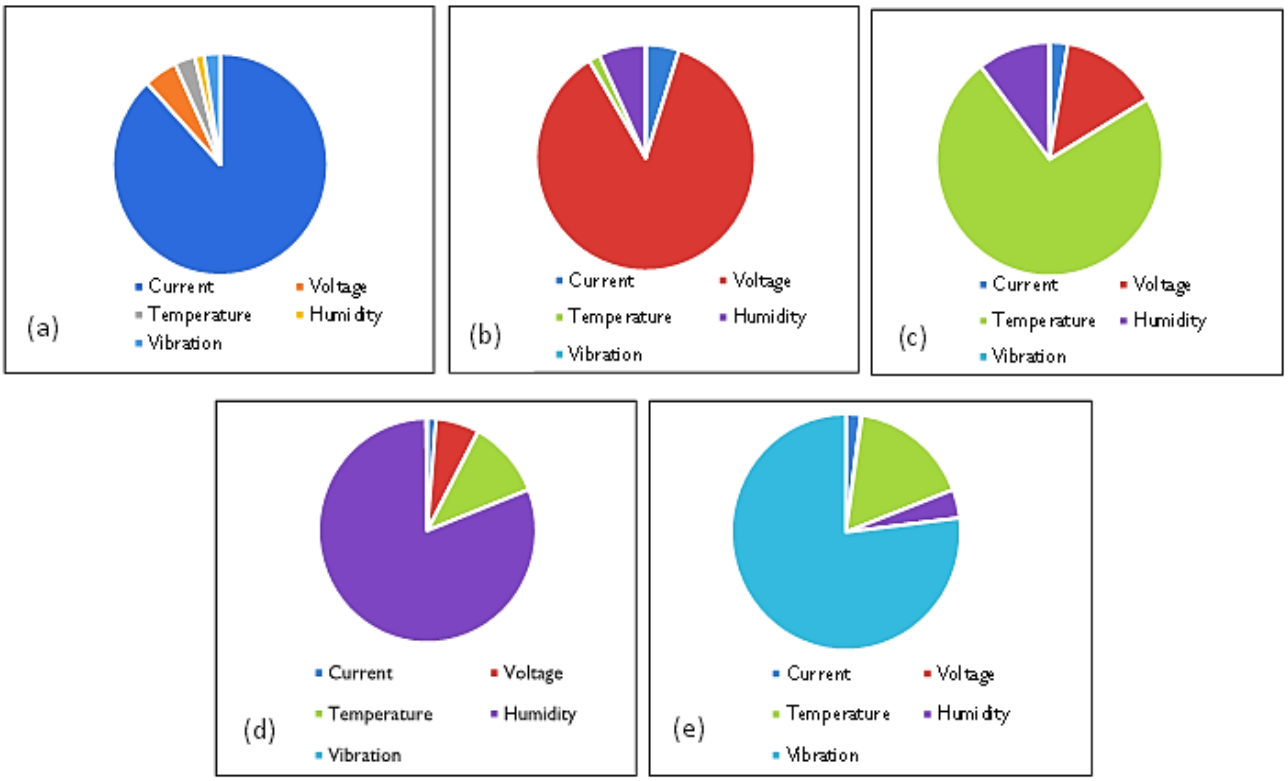


Figure 5: Fault Occurrences for Trained Models (a) Trained Model 1, (b) Trained Model 2, (c) Trained Model 3, (d) Trained Model 4, (e) Trained Model 5.

4. Conclusions

In conclusion, employing machine learning (using Python) to implement predictive maintenance for electric motors turns out to be a very successful and efficient strategy for improving operational reliability and reducing downtime. By employing sophisticated analytics and machine learning algorithms, possible problems can be proactively identified, facilitating prompt intervention prior to a catastrophic failure.

NumPy, pandas, scikit-learn, and other large libraries, along with Python's adaptability, make it a solid tool for feature engineering, data preprocessing, and model building. Leveraging historical data, sensor readings, and relevant parameters, predictive models can be trained to forecast the health and performance of electric motors.

Predictive maintenance optimizes resource allocation and maintenance schedules in addition to lowering unplanned downtime. This strategy minimizes the need for reactive repairs and prevents production interruptions, which results in significant cost savings. Additionally, by prolonging the life of electric motors and minimizing needless resource consumption, it improves the overall sustainability and efficiency of operations.

Predictive maintenance solutions can also be readily modified and enhanced over time thanks to Python's ongoing evolution and the ecosystem that supports it. The system's adaptability is further increased by incorporating real-time monitoring and feedback loops, which enable modifications in response to shifting operating conditions and patterns.

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