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Development of an AI Based AC Motor Fault Prediction Model

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Abstract

Maintaining industrial motors is critical in the manufacturing and mining industries, because motor faults can cause financial losses, including delays and downtime during production. This paper is going to investigate the development of an AC motor fault predictive AI model applicable in industrial settings. AI representing artificial intelligence. The model is trained on data that focus on nature, type and cause of faults in AC motors [6]. The structure and main components of the AC motor will be described separately with their purpose stated, the components are: rotor, stator and bearing, fan blade, wiring cover, end bell and motor frame. The investigation will name and classify types of faults commonly found in AC motors and will analyse current strategies used to resolve these problems of faults in motors including reactive and scheduled maintenance approaches. The motor faults are classified into two types which are electrical faults and mechanical faults [3]. There are two sub classes of electrical faults which are stator faults and rotor faults. Mechanical faults include bearing faults and eccentricity related faults, mainly caused by intense thermal, mechanical and environmental stress [4]. This work shows how the AI model was developed and tested to detect these faults. Most of these faults are really progressive faults which continue to occur on different random occasions. However, the work also demonstrated that while use of AI to solve this problem offers promise it still has a lot of development and innovation work needed. The study shows that the bigger the training dataset, the more accurate and useful the model. In contrast traditional approaches will be still remain costly than the produced model. The dataset is used to train AI algorithms such as Linear Regression, Random Forest Regression and Long Short-Term Memory (LSTM) a deep learning algorithm [7]. The data used consists of stator currents, input power, slip, rotor speed, rotor currents and efficiency. After training, the model will be able to predict the fault to be experienced by the motor, and also provide the estimate of probable predicted time the fault is most likely to occur. Also discussed in this article are the signal processing techniques applied to prepare the data to be used in training the model. The article also outlines the types of signal processing methods used when collecting parameters which are essential for error detection. The signal processing technique we used to monitor the condition of the motor is the FFT (Fast Fourier transform) [8]. The resulting dataset is also suitable to be used for training other machine learning models. This study focuses on data processing, feature generation and model training, contributing accuracy and reliability to maintenance engineering through an AI based AC motor fault prediction model.

Keywords: AC, AI, IOT, Deep Machine Learning, Motor Fault, FFT

1. Introduction

AC motors are a critical component in industrial settings for running operations, making them the heart of all movement in machines. Their wide use in industry is attributed to their strong performance, reliability and adaptability. Motors remain the critical part of modern electrical engineering, enabling the conversion of energy from electrical power to mechanical motion. Given that maintenance is a vital part of all operations as motor faults can cause both financial and time losses during production this paper investigates the development of an AI based AC motor fault prediction model [1]. It looks at nature, type and cause of faults in AC motors, followed by the training of a machine learning model to identify motor faults [1]. There are three main maintenance strategies which include reactive maintenance, scheduled maintenance and predictive maintenance. This study focuses on predictive maintenance strategy, and how it impacts industrial operations. The predictive maintenance strategy uses the actual condition of the equipment to plan what maintenance to be performed and when it should be carried out. Various AC motor components are monitored using real time and non-real time measurements. These measurements assess the condition of the motor, the process is called conditional monitoring [1]. There are multiple different factors that can affect a motor's performance, leading to a maintenance requirement. These factors contribute to various faults associated with AC motors. The most common factors involve electric power, motor vibrations and temperature. Readings can be taken online, this refers to data collected electronically while the machine is running, or offline, during a scheduled maintenance while machine is temporally not running. Deciding what needs to be measured and whether readings are taken online or offline is highly dependent on the size and power of the motor being monitored. It is here that the differences between low and high-powered motors become more apparent. With lower power motors, the failures tend to be due to issues with the bearings, whereas with high power motors, the problems more often in the stator windings and rotor bars, the parts of the motor under the most stress, both electrical and mechanical. An electrical motor converts electrical energy into mechanical motion via electromagnetic induction. The key components include, stator - a stationary outer coil generating a rotating magnetic field when connected to AC power, then the rotor, the rotating component windings induced by the stator's field; then the bearings which reduce friction between rotor and stator, then the enclosure making the wiring cover and motor frame. The condition of these internal active parts usually requires direct inspection and measurement, so inspections are performed offline in addition to the online measurements taken while the machine is running. This development will name and classify types of faults experienced by AC motors, the motor faults are classified into two types which are Electrical faults and Mechanical faults [3]. Electrical faults include subclasses of faults such as stator faults and rotor faults. Mechanical faults include bearing faults and eccentricity related faults, which are mainly caused by intense thermal, mechanical and environmental stress [2]. The study focuses on the building of an artificial intelligence model for predictive maintenance. It explores machine learning methods such as Linear Regression, Random Forest Regression and a deep learning algorithm called long short-term memory [7].

Figure 1. A Graph Diagram Showing the Types of Error and Their Categories

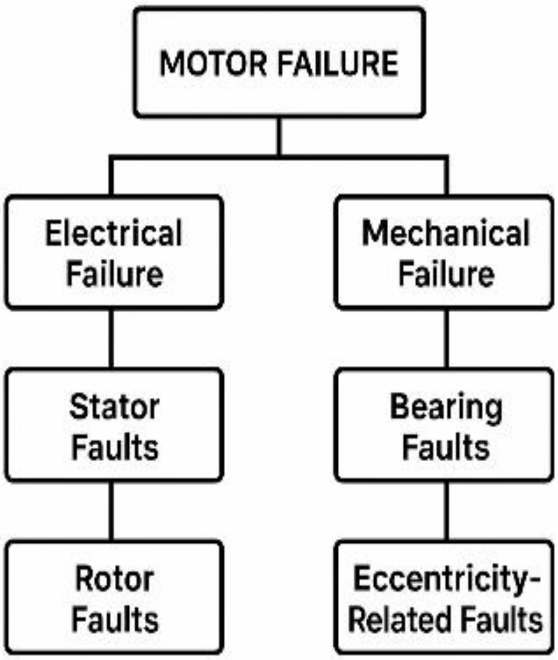
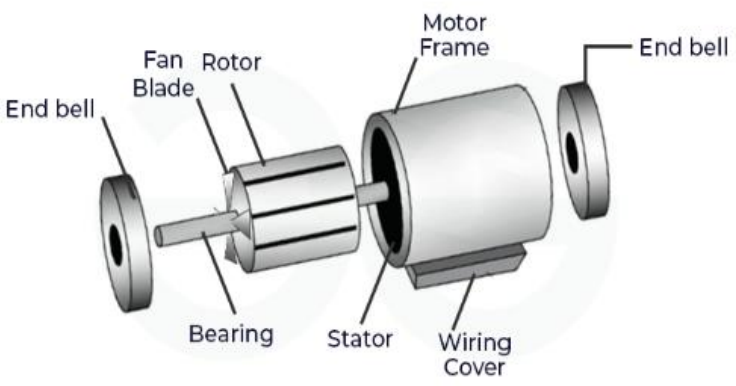


Figure 2. AC Motor Components Image by Geek for Geeks



The Need for AI-based Predictive Maintenance

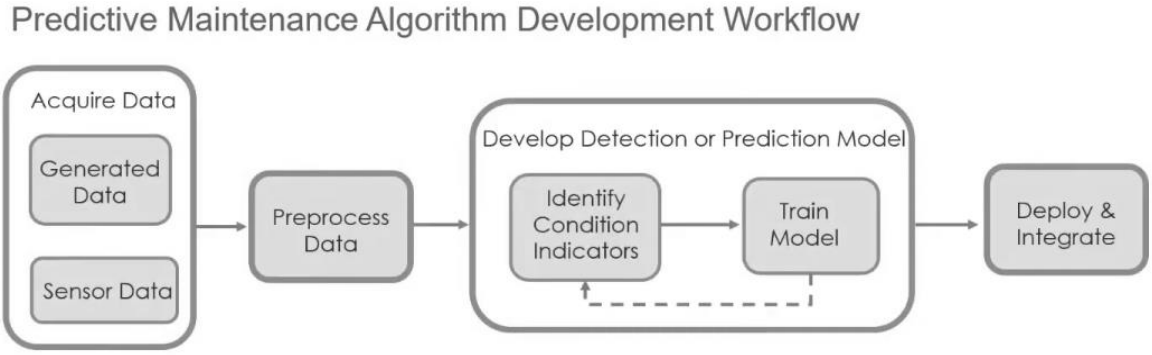
This study proposed machine learning and deep learning methodologies for motor failure prediction, with the aim to improve efficiency as compared to the conventional methods which are heavily dependent on post-failure maintenance strategies. Overall, the paper intends to enable timely motor maintenance before failure thereby reducing costs and disruptions, and increasing production, furthermore the paper shows that AI has demonstrated success in predictive maintenance, predicting motor failure more quickly and accurately, expanding motor lifespan and quality control [5].

2. Related Work

AC motors are reliable and adaptable making them a critical component in industrial operations as they are essential for the conversion of electrical energy into usable mechanical motion. That being said, 'motor related faults can lead to substantial production downtime and financial losses due to maintenance and operational costs. This underscores the need for effective maintenance strategies' [2]. The following chapter reviews existing literature on the use of artificial intelligence in predictive maintenance strategies, investigating methodology, key findings, and identifying gaps that promise further improvements [1]. This chapter aims to set the background and basis for methodologies for developing an AI powered predictive maintenance model that proves the predictability of ac-motor related faults in industrial operations. Conventionally motor maintenance approaches have focused on reactive methodologies, but have since moved to scheduled and recently, as to be addressed, to predictive maintenance approaches [4]. Reactive methodologies are founded on the idea of repairs performed only after a failure has occurred, however this still suffers from unscheduled maintenance strategy and production costs [3]. Scheduled maintenance strategy gives the framework where routine inspections and part replacements occurring at fixed intervals, despite the actual condition of the equipment. However even though this strategy reduces the chances of unforeseen failures, it often leads to unnecessary maintenance and resource wastage [3]. Predictive maintenance is founded on the concept called condition monitoring, which implements an approach of assessing equipment health and predicting potential failures, giving room for maintenance to happen only when necessary, optimizing resources and minimizing unplanned downtime [1]. The use of AI and machine learning in industrial motor maintenance models has further enhanced the underlying capabilities of the maintenance strategies, allowing for more accurate fault detection and prediction [3]. AC motor faults are categorized into electrical faults and mechanical faults. Electrical faults making up stator and rotor related faults and insulation-based failures, on the other side mechanical faults make up bearing faults, eccentricity-related faults, and imbalances. Multiple sensor modalities are used to detect given faults; which includes vibrational analysis, temperature monitoring, and current and voltage monitoring. For collecting the data to be analysed for bearing failure prediction, vibrational sensors are used, while temperature sensors are used to monitor overheating risks. Current and voltage monitoring are central to detecting electrical fault such as stator and rotor failures [2].

3. Methodology

Figure 3. Apredictive Maintenance Algorithm Development Workflow



The research follows an experimental, engineering design focused on the development and evaluation of an AI-based predictive maintenance model for AC motors using Python programing language and Python libraries. The development is carried out using Jupyter Notebook within Google Colab development environment with python programming. The study follows the gathering of sensor data, data processing and feature extraction using the Python Pandas library, which is useful for data handling and preparation. This investigation also involves the training and testing of machine learning and deep learning models using Python library called Scikit-learn, allowing the training of models to predict motor faults. The methodological pipeline starts with data acquisition from sensor data stored in online open databases. The data from AC motors operating in industrial environments comprised of features such as stator and rotor current, vibrations, rotor speed and slip, load current, and winding temperature, capturing both online and offline measurements. This provides a comprehensive dataset reflecting various motor conditions. Online data acquisition uses sensors attached to the motor system to continuously monitor parameters while the motor is still running. Then when the motor is temporarily stopped offline data is usually collected during scheduled maintenance, allowing direct inspection and measurement of internal components such as stator and rotor bars related parameters. The faults are categorized into two, electrical faults and mechanical faults [2]. Electrical faults include subclasses of faults, namely stator faults and rotor faults. Mechanical faults include bearing faults and eccentricity-related faults [3], which are mainly caused by intense thermal, mechanical and environmental stress. The four types of faults we implemented to determine the state of the motor are overload, open circuit fault, closed circuit fault and broken rotor bars.

Figure 4 Dataset Columns

```
[ ] data.head()
```

	Stator currents	Rotor currents	Vibrations	Rotor speed	Slip	Temperature	Load current	Fault type
0	-0.65424	-2.217100	-0.143530	-0.10998	0.39937	0.006615	0.66557	-0.118960
1	-0.66729	0.027002	0.005527	-0.16770	0.47855	0.008733	0.71374	0.084965
2	-0.66265	-1.943300	-0.445160	-0.30202	0.39453	0.006737	0.56121	0.064205
3	-0.65701	0.064340	0.277840	-0.28173	0.47305	0.006269	0.58388	-0.090535
4	-0.67182	-1.265400	-0.572840	-0.35114	0.37129	0.005659	0.38061	0.172730

```
[ ] # Check for missing values
    print(data.isnull().sum())
```

```
Stator currents    0
Rotor currents     0
Vibrations         0
Rotor speed        0
Slip               0
Temperature        0
Load current       0
Fault type         0
dtype: int64
```

Signal Processing and Feature Extraction and model development

To improve the quality and fidelity of data used for AI model training, signal processing techniques are applied, these include Fast Fourier Transform (FFT), which converts signals from the time domain to the frequency domain to identify fault-specific amplitude components and harmonics [8]. Filtering and noise reduction are performed alongside feature engineering which includes the extraction of relevant statistical and spectral features from processed signals, such as peak frequencies, power readings and energy content, that serve as inputs for machine learning models. Three AI algorithms are implemented and compared for fault prediction. First, linear regression is used as baseline model to assess the relationship between sensor parameters and fault occurrence. Then the random forest regression an ensemble machine learning algorithm is used to handle nonlinear relationships and interactions, providing robust fault classification. Lastly, a deep learning model Long Short-Term Memory (LSTM) is implemented, capable of capturing temporal dependencies in sequential sensor data and improving prediction accuracy for progressive faults [7]. The dataset is split into training and testing subsets to evaluate model performance. Cross-validation techniques are employed to prevent overfitting and ensure generalizability.

Figure 5 Data Feature Correlation Heat Map

```
[ ] import seaborn as sns
    plt.figure(figsize=(10, 6))
    sns.heatmap(data.corr(), annot=True, cmap="coolwarm", fmt=".2f")
    plt.title("Feature Correlation Heatmap")
    plt.show()
```

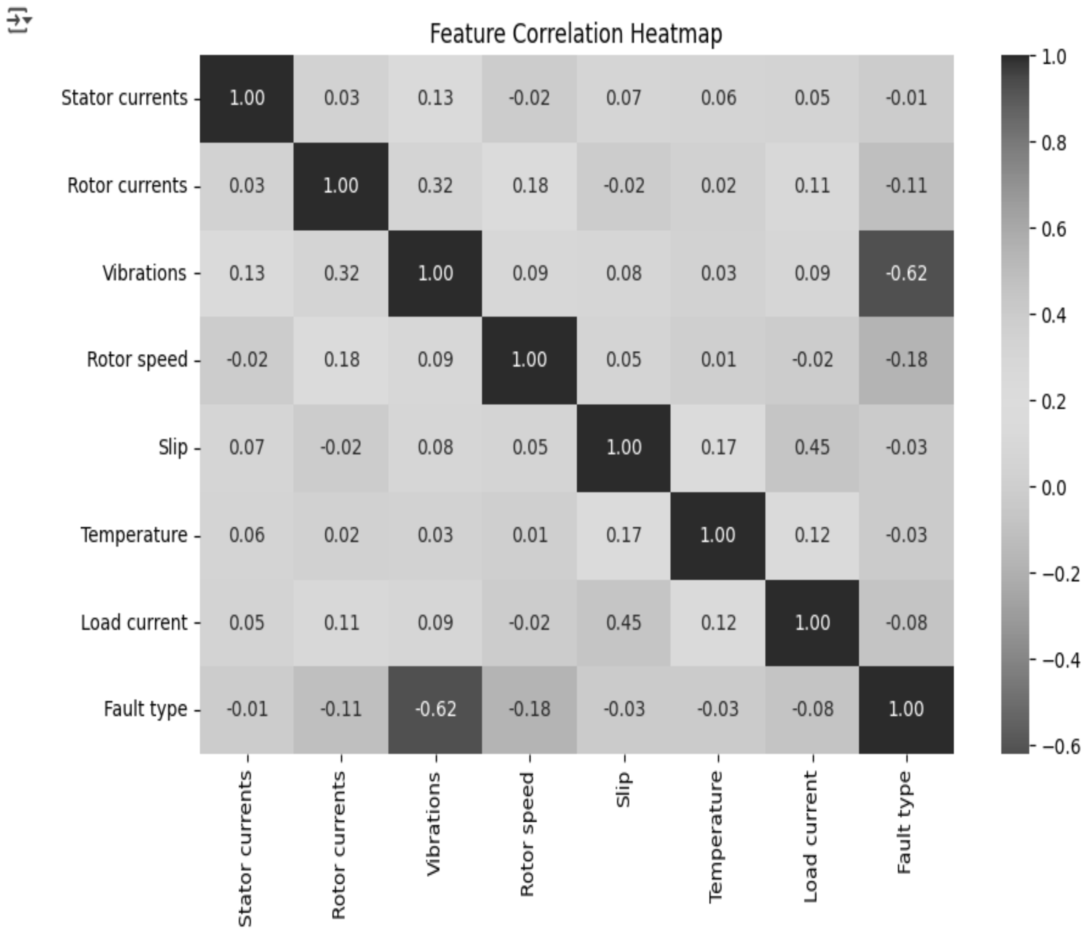


Figure 6 Feature Distributions

```
import matplotlib.pyplot as plt
data.drop("Fault type", axis=1).hist(figsize=(12, 8))
plt.suptitle("Feature Distributions")
plt.show()
```

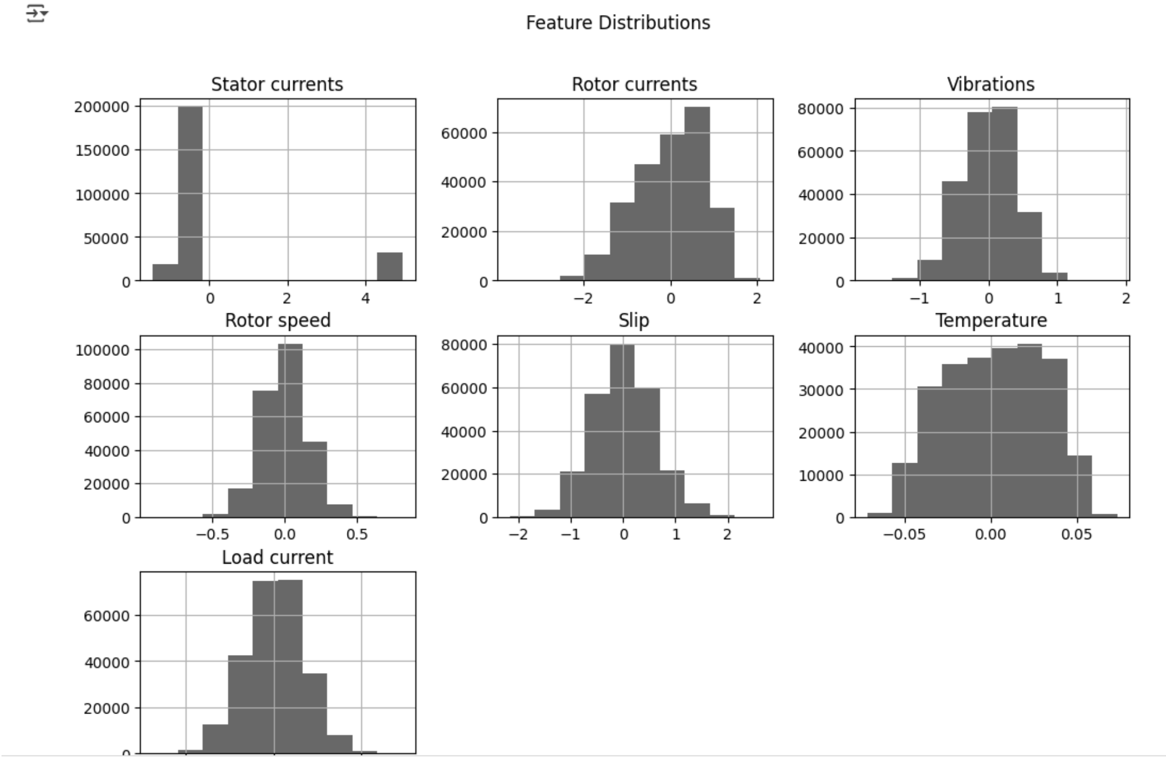
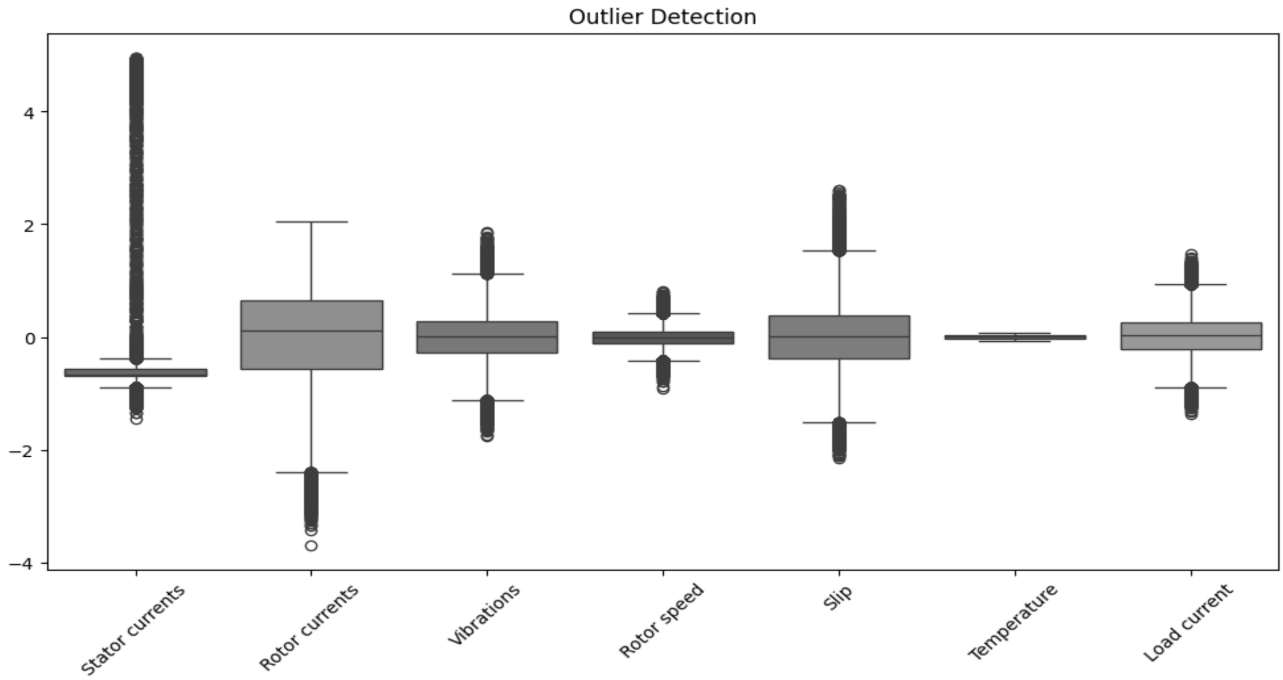


Figure 7 Outlier Dataset Detection Candlesticks



Model Training and Evaluation

Models are trained on labelled datasets, with each instance corresponding to well-defined motor conditions and fault types. The evaluation metrics include accuracy, precision, mean absolute error (MAE), mean square error and R^2 score. The models' ability to predict the timing of fault occurrence is also evaluated. Model performances are compared to identify the most effective algorithms for predictive maintenance applications. For system implementation and integration, the developed AI model is embedded into a predictive maintenance framework that features a Human-Computer Interface (HCI). This interface allows operators to upload sensor datasets and receive fault predictions along with estimated fault occurrence times.

Figure 8. Linear Regression Trained Model Performance

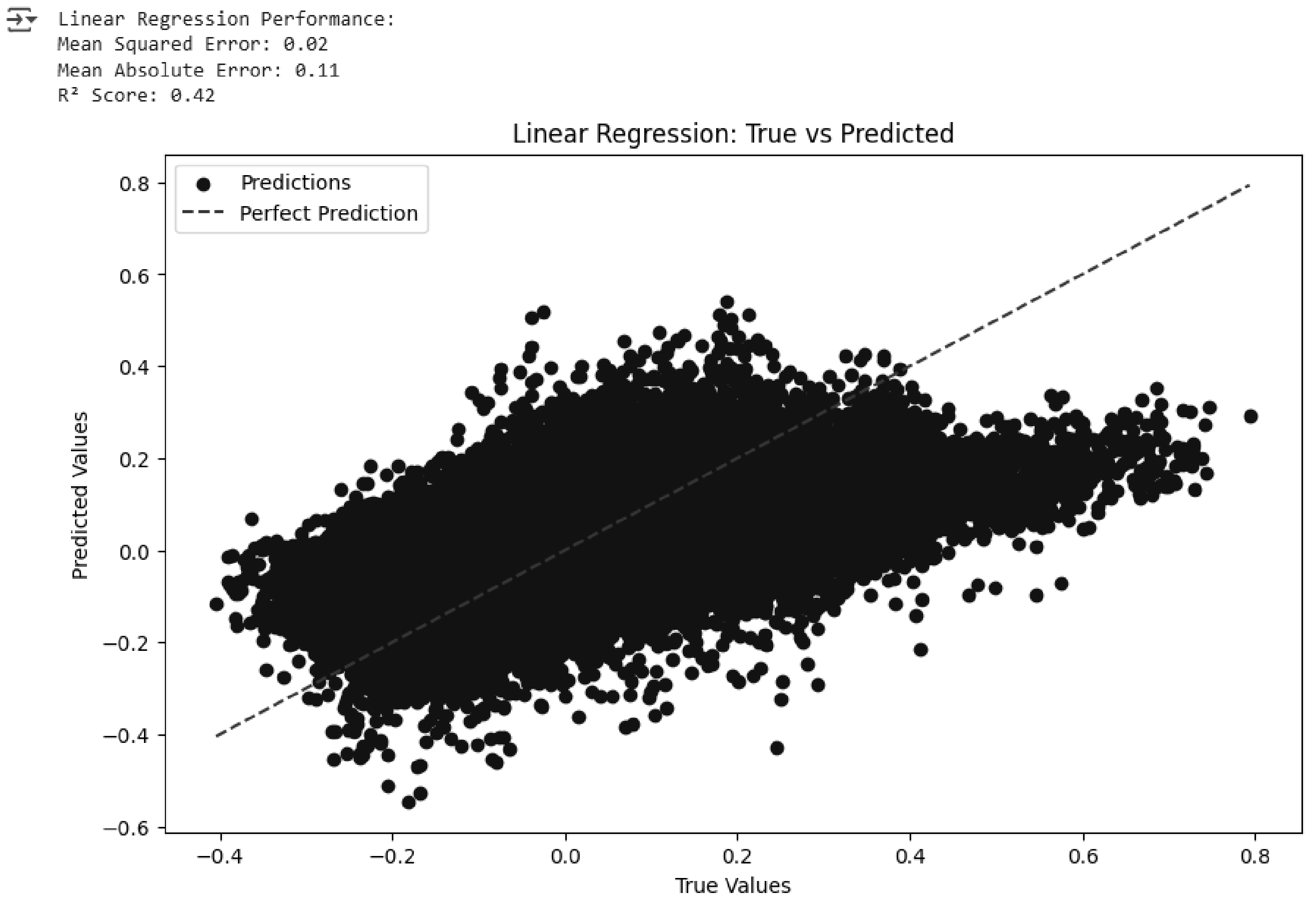


Figure 9. Random Forest Regression Model Performance

```
Random Forest Regressor Performance:
Mean Squared Error: 0.02
Mean Absolute Error: 0.09
R² Score: 0.54
```

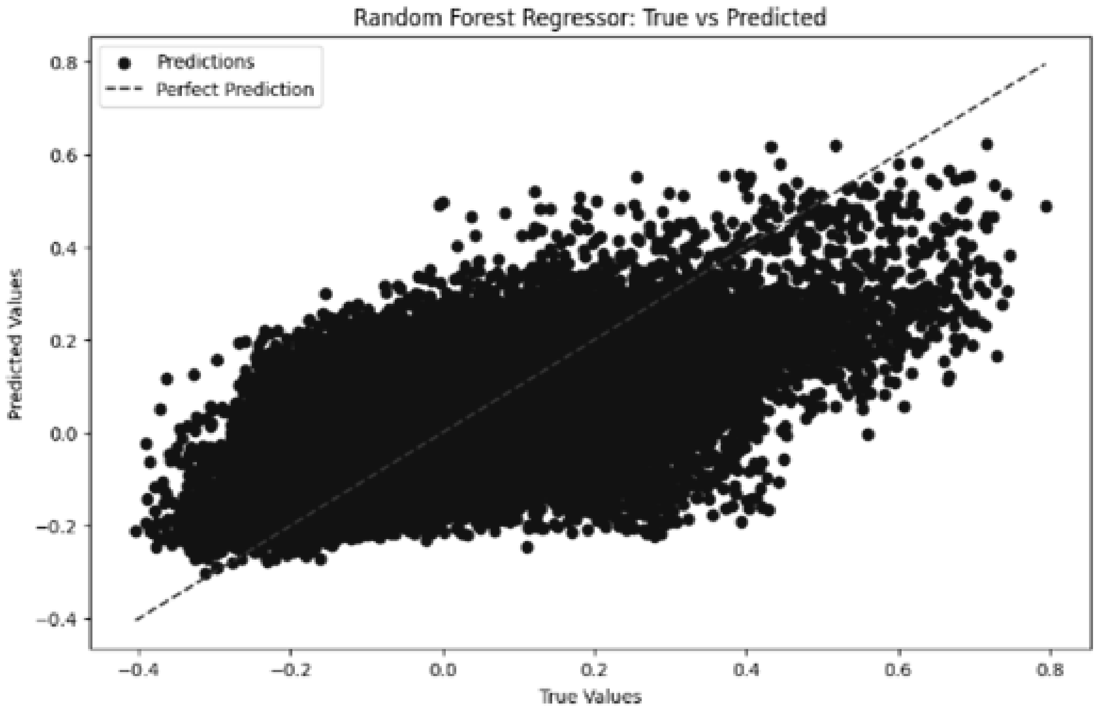


Figure 10. LSTM Model Training

```
plt.title('LSTM: True vs Predicted')
plt.legend(loc='upper left')
plt.show()
```

```
/usr/local/lib/python3.11/dist-packages/keras/src/layers/rnn/rnn.py:200: UserWarning: Do not p
  super().__init__(**kwargs)
Epoch 1/100
6250/6250 ━━━━━━━━━━━━━━━━━━━━ 19s 3ms/step - loss: 0.0174
Epoch 2/100
6250/6250 ━━━━━━━━━━━━━━━━━━━━ 15s 2ms/step - loss: 0.0159
Epoch 3/100
6250/6250 ━━━━━━━━━━━━━━━━━━━━ 21s 3ms/step - loss: 0.0157
Epoch 4/100
6250/6250 ━━━━━━━━━━━━━━━━━━━━ 16s 3ms/step - loss: 0.0154
Epoch 5/100
6250/6250 ━━━━━━━━━━━━━━━━━━━━ 16s 3ms/step - loss: 0.0155
Epoch 6/100
6250/6250 ━━━━━━━━━━━━━━━━━━━━ 20s 3ms/step - loss: 0.0154
Epoch 7/100
6250/6250 ━━━━━━━━━━━━━━━━━━━━ 23s 3ms/step - loss: 0.0155
Epoch 8/100
6250/6250 ━━━━━━━━━━━━━━━━━━━━ 19s 3ms/step - loss: 0.0154
Epoch 9/100
6250/6250 ━━━━━━━━━━━━━━━━━━━━ 17s 3ms/step - loss: 0.0154
Epoch 10/100
6250/6250 ━━━━━━━━━━━━━━━━━━━━ 17s 3ms/step - loss: 0.0154
Epoch 11/100
6250/6250 ━━━━━━━━━━━━━━━━━━━━ 23s 3ms/step - loss: 0.0154
Epoch 12/100
6250/6250 ━━━━━━━━━━━━━━━━━━━━ 17s 3ms/step - loss: 0.0154
Epoch 13/100
6250/6250 ━━━━━━━━━━━━━━━━━━━━ 16s 3ms/step - loss: 0.0153
Epoch 14/100
6250/6250 ━━━━━━━━━━━━━━━━━━━━ 16s 3ms/step - loss: 0.0153
Epoch 15/100
6250/6250 ━━━━━━━━━━━━━━━━━━━━ 16s 3ms/step - loss: 0.0154
Epoch 16/100
6250/6250 ━━━━━━━━━━━━━━━━━━━━ 21s 3ms/step - loss: 0.0154
Epoch 17/100
6250/6250 ━━━━━━━━━━━━━━━━━━━━ 21s 3ms/step - loss: 0.0153
Epoch 18/100
6250/6250 ━━━━━━━━━━━━━━━━━━━━ 16s 3ms/step - loss: 0.0153
Epoch 19/100
```

4. Results and Discussion

The implemented machine learning and deep learning models in artificial intelligence powered predictive maintenance for AC motors used in industrial operations outperformed traditional maintenance strategies and proved more useful [2]. Initially looking at data exploration revealed that there were no missing values in the dataset. While histograms, correlation heat maps, and boxplots provided insights into feature distributions, relationships between variables and the presence of outliers. The datasets used for this research included critical AC motor parameters: stator currents, rotor currents, vibrations, rotor speed, slip, temperature, load current and fault. Feature selection and scaling were performed, the dataset split into training (80%) and testing (20%) sets. Three models were trained and evaluated. These models include Random Forest Regression, LSTM network and Linear Regression. The random forest regression achieved the following performance metrics, mean squared error (MSE):0.02, mean absolute error: 0.09 and R^2 of 0.54 indicating that Random Forest Regression explains approximate 54% of the variance in the fault type. The plot true versus predicted on the values shows the models predictions which are close to their actual values. The LSTM network also achieved MSE of 0.02 and MAE of 0.11, with R^2 of 0.53 indicating that it explains 53% of variance. Linear regression model has lower R^2 compared to other models indicating that it explains less variance in the data. The Random Forest Regression and the LSTM network performed similarly, with slightly better R^2 scores compared to linear regression this showed that the relationship between features and the fault type variable is likely to be nonlinear, showing that Random Forest and LSTM models are more likely to be equipped to capture. The results support the growing body of evidence that AI powered predictive maintenance could provide actionable insights for industrial operations, making possible early detection of faults and more effective scheduled maintenances, helping organizations reduce unplanned downtime, while optimizing maintenance resources, extending equipment lifespan [7]. Despite the promising results, challenges still exist. The transition from regression to classification modelling is necessary for operational deployment. Also, to be addressed are issues with data integration, system compatibility and human factors are important to be addressed for successful adoption of AI-driven predictive maintenance solutions. Looking at the comparable performances shown between the Random Forest Regression algorithm and the Long Short Term Memory network, important distinctions shown in the nature of predictions from the provided analysis. Though both models achieved similar R^2 values (0.54 and 0.53 respectively), however the random forest model has demonstrated greater robustness against data that was filled with noise and outliers of the input data during training. The robustness of the mentioned algorithm direct benefits from a mechanism that reduces overfitting and stabilizes variance across the decision trees the mechanism is called averaging mechanism. However, the LSTM network demonstrated a powerful and stronger capacity to take snapshots of subtle trends and temporal dependencies embedded in time series sequences, working mostly where progressive faults are common such include bearing wear or gradual misalignment. This capability of temporal forecasting is quite important and gives an advantage when anticipating faults that are slow developing which are not immediately evident from static captures of sensor data. Equally important was the change in the type of explainability provided with each model. Random Forests, for instance, allow the user to specify one of the features as Rotor Slip or Intensity of Vibration and calculate the importance that feature has in the model's results. Explanatory power is important in industrial cases when maintenance personnel need, not, only the prognosis, but also the reason which is helpful in discerning or deciding what to inspect or act upon. On the other hand, LSTMs offer no trace of how decisions are made; further methods like SHAP (Shapley Additive explanations) or attention needs to be integrated to explain the outcome [7]. Though they enhance explainability, these tools also complicate the pipeline. From a data perspective, the choice of pre-processing techniques, such as Savitzky-Golay smoothing, Z-score normalization, and outlier exclusion was essential to model achievement. The large volume of data from the sensors also increases their variance for over fitting which can become an issue especially for deep learning models [4]. Not using dimensionality-reducing techniques helped preserve all the features which was a good decision as it retained physical interpretability [2]. This is very important for electromechanical systems where domain knowledge has to guide model validity.

5. Conclusion

The research investigated the use of AI and machine learning models for predictive maintenance of AC motors using real world sensor data. The investigation proved that Random Forest and LSTM models could explain a significant portion of the variance in motor faults, outperforming traditional linear regression, reinforcing the value of AI in predictive maintenance strategies for improving equipment reliability, reducing downtime and optimizing maintenance operations. However, the study also showed that the importance of problem framing was critical: treating fault type as a categorical variable and employing classification models would be essential for practical implementation. Follow up research is to focus on advanced feature engineering, and system integration to fully realize the benefits of AI-powered predictive maintenance.

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7. Authors' Biography

Tanaka Mutsvangwa is a passionate industrial engineering masters, student with some experience working in industry, he completed his bachelor's degree at Harare Institute of Technology.

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