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Smart Maintenance System (SMAT): Predictive Maintenance of Electrical Motor Applications

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ABSTRACT

Electrical motor failures can lead to unexpected downtime, increased maintenance costs, and reduced operational efficiency in industrial applications. Traditional maintenance strategies, such as reactive and scheduled maintenance, often fail to prevent unexpected failures efficiently. This study presents a Smart Maintenance System (SMAT) designed to optimize motor maintenance through predictive techniques. Utilizing mechanical vibration, electrical current, and motor body temperature sensors, the system continuously monitors motor conditions in applications such as pumps and generators, enabling early fault detection and reducing operational disruptions. Sensor data is transmitted via Raspberry Pi using the TCP/IP protocol and stored on a programmable interface controller. MATLAB is employed for data preprocessing, modeling, and prediction. A comparative analysis of K-Nearest Neighbour (KNN) and Artificial Neural Network (ANN) algorithms shows classification accuracies between 92.6% and 95.8% for normal and failure conditions. Future enhancements will focus on real-time data collection and improved predictive capabilities.

1. INTRODUCTION

Predictive maintenance (PdM) is a proactive maintenance strategy that utilizes real-time monitoring, historical data, and predictive analytics to assess the condition of equipment and anticipate potential failures before they occur. Unlike reactive maintenance, which addresses issues after failure, or preventive maintenance, which follows scheduled inspections, PdM relies on data-driven insights to optimize maintenance timing, reduce downtime, and extend equipment lifespan.

Electrical motors are fundamental components in industrial systems, powering critical applications such as pumps, conveyors, and generators. Unexpected motor failures can lead to costly downtimes, production delays, and increased maintenance expenses. Traditional maintenance approaches, including reactive (repairing after failure) and periodic scheduled maintenance, often fail to address faults proactively, resulting in inefficiencies and operational risks [1][2]. Figure 1 illustrates various maintenance approaches in the general maintenance methods. Reactive maintenance is a method that repairs the motor when it breaks, while periodic maintenance refers to activities performed on the motor based on a set time interval. For proactive maintenance, it is a maintenance strategy that corrects the root causes of underlying motor conditions. Predictive maintenance is the best of all the maintenance solutions since it may enhance the manufacturing process of the motor while lowering expenses. On the other hand, predictive maintenance (PdM) is an important strategy for motor maintenance. This is due to electric motors having a significant influence on almost every aspect of modern living. Automobiles, engines, and machines in the factory all use electrical motors to convert electrical energy into mechanical energy which can be used. In addition, electrical motors are also used in a vast number of industrial activities [3]. Therefore, PdM is deserving of concern to prevent any disruptions.

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The majority of industrial manufacturing processes and equipment depend on electrical motors. Therefore, these machines deserve consideration in order to improve the efficiency of the manufacturing process [4]. However, most of the electrical testing is performed as an off-line test, this state that component is required to be out of service to perform the testing. Yet, because of the hectic working schedules, many mission-critical industries may not be available for scheduled maintenance of their equipment. When any fault identified with off-line testing is being detected with the equipment out of service, the equipment's availability will become a concern [5]. Due to technological and logistical limitations, maintenance cannot always be performed everywhere. Machine failures during production can lead to adverse effects on the production schedule, delivery delays, or employee overtime to compensate for the loss. As such, the predictability of a component failure during off-line testing is only as good as the extrapolated estimate [6].

Predictive maintenance faces challenges such as ensuring data quality, integrating models with existing systems, and managing high implementation costs. Real-time processing of large datasets and maintaining model accuracy over time are also significant hurdles, especially with diverse machinery and unpredictable equipment behavior[7]. Addressing these issues requires robust strategies to enhance its adoption and effectiveness[8][9].

This paper aims to develop a smart maintenance system (SMAT) for effectively detecting abnormalities in electrical motors, along with a robust data acquisition system using an open-source programming tool. The performance of the K-Nearest Neighbour (KNN) and Artificial Neural Network (ANN) algorithms in a predictive preventive maintenance system will be compared. By achieving these objectives, this research contributes to advancing predictive maintenance techniques for motors, improving reliability, and extending operational lifespan. The findings will enhance motor health monitoring, enabling proactive maintenance interventions and reducing unexpected failures. This study contributes to optimize motor performance in industrial applications.

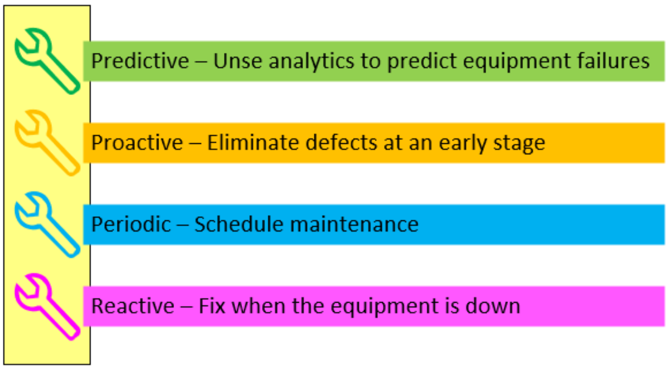

Fig. 1. Type of maintenance

2. Predictive Maintenance with Data Driven Approach in Industrial Electrical Motor

First, confirm that you have the correct template for your paper size. This template has been tailored for output on the A4 paper size. If you are using US letter-sized paper, please close this file and download the Microsoft Word, Letter file Data-driven methods play a crucial role in failure identification and predictive maintenance, utilizing data analysis and statistical techniques, including machine learning algorithms. These methods leverage the power of training to create predictive models based on extensive historical data[5,6]. By analyzing patterns and relationships within the data, these models can provide valuable insights into the likelihood of device failures and their anticipated lifespan. The process begins with training the model using a vast amount of historical data, allowing it to learn patterns and correlations that indicate potential failure events. Once trained, the model is tested and verified using additional data to evaluate its predictive capabilities. This testing phase helps assess the model's accuracy and reliability in making predictions about future failures.

Samhouri et al. [10] presented an Adaptive Neuro-Fuzzy Inference System (ANFIS) and a Neural Network system (NN) to analyze and predict errors. By employing a signal connected to motor status and failure type, they utilized specific signal properties as inputs to the ANFIS and neural nets, yielding anticipated failure type results. Another approach proposed by Giantomassi et al. [11] involved a Kernel Density Estimation (KDE) and Kullback-Leibler divergence-based technique for electrical motor forecasting. They used Kullback-Leibler divergence as an indicator to measure the dissimilarity between two probability distributions, while KDE was employed to assess the probability density functions of both healthy and malfunctioning motors. In a study by Jawadekar et al. [12], the wavelet transform was utilized to analyze motor line currents, and a feedforward Artificial Neural Network (ANN) was employed to characterize faults. They relied on extracted flaw aspects using the Continuous Wavelet Transform (CWT) from the line current signals. Furthermore, a signal-processing condition was applied to distinguish between normal and fault situations, enabling the feedforward ANN to classify various defects in an induction motor. Yang et al. [13] proposed the Shock Pulse Method (SPM) for electrical motor condition monitoring. This method involved analyzing real-time frequency spectrum and vibration data to identify faulty motors. In the time-domain analysis, statistical metrics such as root mean square, kurtosis, skewness, and crest factor were considered, while the frequency spectrum provided by the SPM equipment pinpointed the defective motors. Biswal et al. [14] constructed a bench test equipment to simulate a wind turbine's working state for motor condition testing. They collected vibration data under both normal and damaged conditions by replacing a normal component with a damaged one. The researchers used ANN predictions to differentiate between features of a normal condition and those of a faulty one, achieving a categorization accuracy of 92.6 percent in their study.

In more recent projects, researchers have shown a propensity towards the utilization of genetic algorithms. For instance, Chen et al. [15] introduced a rolling bearing defect diagnostic technique by combining resonance-based sparse signal decomposition (RSSD) and wavelet transform (WT). Similarly, He et al. [16] proposed an unsupervised failure diagnostic technique based on a deep belief network (DBN) for gear transmission chain failure. Notably, these projects incorporate genetic algorithms to enhance failure identification alongside data pre-processing or parameter tuning of the training algorithm. Another notable approach is presented by Gou et al. [17] who suggested a data-driven fault diagnosis approach using a genetic algorithm (GA) in conjunction with a support vector machine (SVM). The GA is employed to optimize the parameters of the SVM, resulting in the best classification model. Similarly, Kiangala et al. [18] implemented advanced programming features of a Siemens S7-1200 programmable logic controller (PLC) to control a bottling plant. Real-time evaluation of vibration speed data from a sensor attached to the conveyor motor enables the automatic identification of early motor risks based on ISO 2372 vibration severity criteria.In the realm of real-time monitoring, Syafrudin et al. [19] proposed a method that combines sensors from the Internet of Things (IoT), big data processing, and a hybrid prediction model. By incorporating noise-based outlier identification and random forest classification, this hybrid model offers improved accuracy in identifying faulty motors. Similarly, Rosli et al. [20] developed an Artificial Neural Network (ANN) model for predictive maintenance of Air Booster Compressor (ABC) motor failure. They emphasized the importance of optimizing the ANN's weights and employed a Feedforward Neural Network (FNN) to handle complex parameters in nonlinear modeling. Lastly, Manfre [21] advocates for the use of Data-Driven Modeling (DDM) in predictive maintenance, which allows for the application of different specific models to each reported class. The technology employed in this approach, including accelerometers and machine learning models, enables the detection of anomalies by sensing vibrations on an electrical motor's spinning shaft.

In summary, the field of predictive maintenance has witnessed significant advancements through the integration of data-driven methods and machine learning techniques. Researchers have explored various approaches, ranging from statistical algorithms like KNN and ANN to genetic algorithms, kernel density estimation, wavelet transform, and deep belief networks. These techniques enable the analysis of sensor data and the prediction of failures in different motor systems. Furthermore, the combination of IoT sensors, big data processing, and hybrid prediction models has shown promise in real-time monitoring and fault detection. The optimization of model parameters, such as weights in neural networks, plays a crucial role in achieving accurate predictions. Overall, these research efforts contribute to the development of robust predictive maintenance systems, enabling early detection of motor faults, efficient maintenance planning, and improved operational reliability. With further exploration and refinement of these approaches, the field of predictive maintenance is poised to make significant strides in enhancing equipment performance, reducing downtime, and optimizing maintenance strategies for various industries.

3. METHODOLOGY

3.1 Maintaining the Integrity of the Specifications

In this work, we focus on three key inputs for our predictive maintenance system: motor vibration sensing, motor current sensing, and motor temperature sensing. These inputs serve as crucial indicators for monitoring the performance of the electrical motors , generators etc. [22]. While there are other measurements, such as motor torque, speed and particle in motor oil can be considered, we have intentionally limited our scope to these only fundamental elements of industrial electrical motor sensing. Our objective is to validate the effectiveness of the predictive system using these primary sensor inputs before exploring potential enhancements in future iterations. By concentrating on these core parameters, we aim to provide a clear and focused evaluation of the predictive maintenance system's capabilities.

The selection of the main controller is using a Raspberry Pi single-board computer. The Raspberry Pi platform offers high computational power, adaptability, and a wide availability of Python function libraries. These features provide a solid foundation for developing complex applications and implementing advanced functionalities. Secondly, the Raspberry Pi is known for its low power consumption and cost-effectiveness. These characteristics make it an attractive choice for building devices that are not only energy-efficient but also affordable, resulting in low-cost and long-lasting nodes[23]. Considering these factors, the Raspberry Pi emerges as the ideal platform for the construction of the system prototype in this paper.

There are many different sensors available in the market, each with its own advantages and limitations. Therefore, we have taken special care to choose sensors that are well-suited for our specific application. We consider factors such as how selective the sensor is, the range it can measure, how sensitive it is, and how reliable and durable it is. These characteristics are important because they affect the accuracy and quality of the data we will use for our analysis. By carefully selecting the right sensors, we can ensure that we have reliable and accurate information to perform a thorough analysis. Mechanical vibration measurement is based on the GY-6500 (InvenSense, USA) sensor with configurable measurement. This sensor features a low-power, low-cost 6-axis Motion Tracking chip (MPU6500) at its core, combining a 3-axis gyroscope, 3-axis accelerometer, and Digital Motion Processor (DMP) in a compact 4mm x 4mm board. The sensor was chosen for vibration measurement due to its high sensitivity, three-axis motion tracking, and ability to detect early mechanical imbalances or misalignments. On the other hand, to measure current stability and variations in relation to the electrical motor load, an INA219 (Texas Instrument, USA) current sensor is utilized. This sensor operates by measuring voltage across a precision amplifier and a 0.1-ohm shunt resistor with 1% precision. It has a measurement range of +-3.2 A and a resolution of 0.1mA. The sensor is highly precise, compatible with microcontrollers, and communicates data via the I2C protocol. It can be conveniently powered by the Raspberry Pi 4 Model B without requiring an additional voltage source. To measure the motor temperatures, the MLX90614 (Melexis, Belgium) infrared temperature sensor is employed based on non-contact temperature sensing. This sensor incorporates a 17-bit analogue to digital converter and a powerful digital signal processor for temperature detection. It is capable of monitoring both ambient and object temperatures from a distance. The sensor has a temperature range of -40 to 85°C for ambient temperatures and -70 to 382.2°C for object temperatures, with data communication facilitated through the I2C protocol.

We employ a small motor as a representative model, chosen to emulate the behavior of larger motors commonly used in industrial applications. While the selected motor is of smaller size, its specifications closely resemble those of larger counterparts, allowing us to investigate and analyze key performance aspects in a controlled and manageable manner. The AC induction motor (GH 30, Malaysia) used in our research operates with a 240V AC input and has a power rating of 200W with maximum speed of 1400 RPM, making it suitable for examining various predictive maintenance techniques. By studying this scaled-down motor, we aim to gain valuable insights and develop practical strategies that can be applied to larger motors found in real-world industrial settings. Figure 2 shows the proposed system.

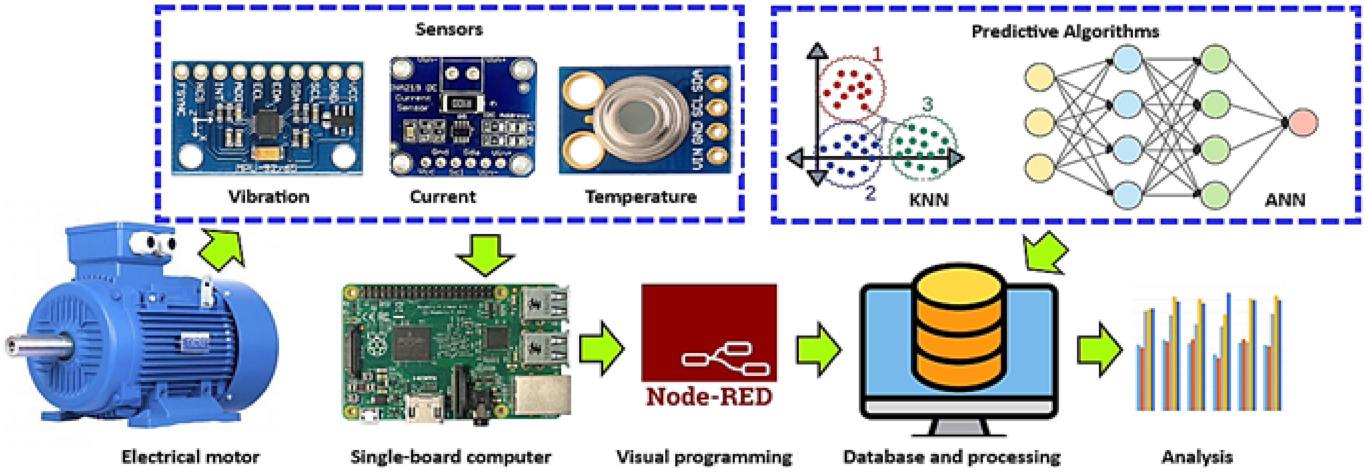

Fig. 2. SMAT System Architecture

3.2 Data and Signal Processing

Data selection step plays a crucial role in handling and analysing data to enhance understanding and interpretation. In this project, we gather diverse data from sensors, which are then translated into easily understandable forms and stored in a database. This data will be utilized in creating future machine learning models. Data is collected every minute over the course of an hour for both normal and abnormal conditions. We have obtained 8 sets of data, with each set comprising 60 sample data points. In total, 480 sample data points were used for training the model, while an additional 80 sample data points were collected for testing purposes. The different conditions for each dataset are summarized in Table 1.

To simulate abnormal motor conditions, we introduce stress in the form of an additional load, specifically a braking system, intermittently applied to the motor shaft throughout the experimental duration. This deliberate application of stress leads to observable changes in both current and temperature readings, providing valuable insights into the dynamic behavior of the motor under stress conditions. Furthermore, to capture abnormal vibration data, an external vibrator system is incorporated into the experimental setup. This system is strategically employed to induce motor failure conditions, generating vibration patterns that can be analyzed. The resulting data from both the stress-induced changes and abnormal vibrations contribute significantly to the comprehensive dataset required for a thorough analysis. The primary objective of employing this approach is to gather pertinent information for the development of a robust predictive maintenance system.

To simulate motor failure conditions for data collection, we carefully replicate real-world scenarios using controlled setups. For vibration failures, we use a shaker operating at frequencies up to 10 kHz, placed near the motor shaft bearing, to replicate the characteristic vibrations caused by bearing faults. The data is captured using a high-precision vibration sensor mounted on the motor housing. For load instability failures, a custom braking system is employed to impose varying loads on the motor, causing current spikes that simulate unstable operating conditions. These current fluctuations are monitored and recorded using a current sensor integrated into the motor's electrical circuit. To simulate temperature-related failures, heat is applied near the motor body using a controlled heating element. A temperature sensor affixed to the motor casing measures the resulting temperature rise, mimicking thermal stress conditions often experienced during motor operation. The data collected from these simulations vibration, current, and temperature is stored chronologically and used to train and validate the predictive maintenance algorithms. This comprehensive approach ensures the system can accurately identify and predict potential motor failures across various failure modes. By carefully simulating and studying motor failures under the controlled conditions, we aim to enhance our understanding of the potential failure modes, for the creation of an effective and reliable predictive maintenance strategy.

Table 1. Electrical Motor Conditions Data

Data set	Conditions		
	Vibration	Temperature	Current
1	×	×	×
2	×	×	✓
3	×	✓	×
4	×	✓	✓
5	✓	×	×
6	✓	×	✓
7	✓	✓	×
8	✓	✓	✓

*✓ = Normal condition
× = Abnormal condition

3.3 SMAT Predection Model

The prediction models in this report utilize historical labeled data, which contains information about past equipment failures, for the purpose of training and testing [24].]In cases where both input and output variables are available, supervised learning algorithms are employed using the training dataset. These algorithms enable the learning of a mapping function from the input variables to the output variables. The aim is to approximate this mapping function with new input data in order to predict the corresponding output variables. sensor inputs before exploring potential enhancements in future iterations. By concentrating on these core parameters, we aim to provide a clear and focused evaluation of the predictive maintenance system's capabilities.

We utilized the K-Nearest Neighbour (KNN) and Artificial Neural Network (ANN) classification methods, with a training and testing ratio of 90:10. The models with the highest accuracy and shortest training time were selected. For KNN, the distance and k variable were adjusted, with two different distances used. The number of neighbours was limited to ten. The ANN employed a feed-forward architecture with three inputs and one output, using the sigmoid function as the activation function. Parameters such as the number of neurons, learning rate, momentum, and epoch were optimized. A comparison was made between the KNN and ANN models to determine their suitability for the research to be optimized is changed while the other two parameters remain constant. Other machine learning models, such as Support Vector Machines (SVM) and Decision Trees, were not considered in this study due to specific limitations in handling the dataset and application requirements. SVM, while effective for high-dimensional data, can be computationally expensive and less efficient when dealing with real-time predictive maintenance, where quick decision-making is essential. Decision Trees, on the other hand, tend to overfit small datasets and may not generalize well without extensive pruning or ensemble methods like Random Forest. KNN was chosen due to its simplicity, effectiveness in small datasets, and ability to classify motor conditions based on similarity metrics without requiring complex training. ANN, on the other hand, was selected for its strong capability in recognizing patterns in nonlinear datasets and providing high accuracy in predictive tasks. Both models were compared to assess their classification performance to determine which model is suitable for this application.

3.4 SMAT Prediction Model by K-Nearest Neighbour (KNN) Model

The K-Nearest Neighbour (KNN) method is a supervised machine learning (ML) technique commonly used for solving classification problems [25]. It is a straightforward and widely used approach due to its simplicity and computational efficiency. In the case of classification and regression problems, the KNN algorithm selects the k nearest datasets from the training dataset based on their proximity to the test dataset. The output of the algorithm depends on whether KNN is employed for classification or regression [26]. To make predictions, the KNN algorithm identifies the k nearest samples to a given test sample and assigns the test sample to the majority class among those k samples. Calculating the distance or similarity between all training samples and each test sample is necessary to determine the k nearest neighbors.

For the Equation for Euclidean Distance, the primary step in KNN is calculating the distance between the data points. For two data points as shows in below equations

$$x = (x_1, x_2, \dots, x_n) \tag{1}$$

$$y = (y_1, y_2, \dots, y_n) \tag{2}$$

The Euclidean distance $d(x, y)$ is given by the following equation

$$d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{3}$$

Where, x_i and y_i are the feature values of the data points x and y, respectively, n is the number of features (sensor measurements like vibration, current, and temperature).

For the KNN Classification, once the distances are computed, the next step is to find the 'k' nearest neighbors and classify the new data point based on the majority vote of its neighbors. The class label C of the new data point x is determined as

$$C(x) = MajorityVote(\{C(x_1), C(x_2), \dots, C(x_k)\}) \tag{4}$$

Where, $C(x_1)$,$C(x_2)$,…,$C(x_k)$ are the class labels of the k nearest neighbors.

The KNN method is a popular choice for classification tasks, offering simplicity and efficiency in predicting outcomes based on the proximity of data points. The classification learner app of MATLAB was used in the work, to determine the best model for the electrical motor failure prediction condition using the datasets conditions presented in Table 1. The medium KNN and cubic KNN was implemented and the differences on its performance classification accuracy is compared.

3.5 SMAT Prediction Model by Artificial Neural Network (ANN) Model

The Artificial Neural Network (ANN) is a mathematical model inspired by biological neural networks. It consists of an input layer, hidden layers, and an output layer. The connections between nodes in an ANN are nonlinear and established through weighting functions [27]. Each neuron in the ANN is connected to the weights of the subsequent layer. The hidden layer serves as a universal approximator, utilizing a non-linear activation function. Neurons apply transfer functions to their inputs, which are the weighted sums of their inputs. For the Equation for the Output of a Single Neuron;

Let $x = (x_1, x_2, \dots, x)$ represent the input to a neuron, and w = ($w1, w2, \dots, wn$) represent the weights associated with the inputs. The output y of the neuron is computed as

$$y = f(\sum_{i=1}^{n} w_i x_i + b) \tag{5}$$

Where, b is the bias term, f is the activation function (commonly the sigmoid function $f(z) = \frac{1}{1+e^{-z}}$, or the ReLU function f(z) = max (0,z)).

For the ANN Model Training;

The training process involves adjusting the weights using backpropagation to minimize the error between the predicted and actual motor condition. The error function used in this study is the Mean Squared Error (MSE), which is defined as

$$MSE = \frac{1}{m} \sum_{i=1}^{nm} \left(y_{pred}^{i} - y_{true}^{i}\right)^2 \tag{6}$$

Where, m is the number of training samples, y_{pred} is the predicted output for sample i, y_{true} is the true output for sample i. The backpropagation algorithm updates the weights and biases to minimize this error using gradient descent as

$$w_i \leftarrow w_i - \eta \frac{\partial MSE}{\partial w_i} \tag{7}$$

where, η is the learning rate. By concentrating on these core parameters, we aim to provide a clear and focused evaluation of the predictive maintenance system's capabilities.

The Artificial Neural Network (ANN) model was implemented using MATLAB/Neural Network Toolbox to predict motor failures. The ANN model was trained and tested using the datasets conditions presented in Table 1. The datasets were divided into training (90% of the total data) and testing (10% of the total data) sets. Two different algorithms, namely the Scaled Conjugate Gradient and Levenberg-Marquardt algorithm, were used to train one neural network. Their performance was compared, and ten hidden layers were employed.

3.6 Data Collection and Model Training

Sensor placement is crucial in predictive maintenance applications. Proper placement ensures accurate data collection, enabling early fault detection and proactive maintenance. Sensors strategically positioned minimize interference and capture subtle changes, preventing major breakdowns and reducing costs [28]. Continuous monitoring with well-placed sensors supports condition-based maintenance, optimizing resource utilization. Accurate data informs decision-making for effective asset management and future maintenance predictions. Sensor placement plays a vital role in accurate data collection, early fault detection, and optimizing maintenance activities in predictive maintenance applications [29].

The best placement for a mechanical vibration sensor in electrical motor monitoring for predictive maintenance is typically on the motor housing or the motor bearing or near the motor shaft [30]. These locations enable effective measurement of vibrations, providing valuable insights into the motor's condition and potential issues. Monitoring the motor housing captures overall vibration behavior, while placing the sensor near the bearing or the shaft allows for specific monitoring of shaft vibrations, offering insights into rotational dynamics and potential problems [30].

For the current sensor is typically near the power supply input or within the motor control circuitry. These positions allow for direct measurement of current flow, providing valuable insights into motor operating conditions and detecting abnormalities or inefficiencies. Monitoring the overall current consumption at the power supply input and integrating the sensor within the motor control circuitry enable detailed analysis of current variations during different operational states, aiding in the detection of motor malfunctions or suboptimal performance.

Meanwhile, a common location for the temperature sensor monitoring includes near the stator winding to detect overheating and insulation degradation, and near the motor bearings to identify bearing issues such as excessive friction or failures [31]. Monitoring temperatures in these areas enables timely maintenance interventions to prevent motor damage and ensure optimal performance. Figure 3 shows the sensors proposed positions.

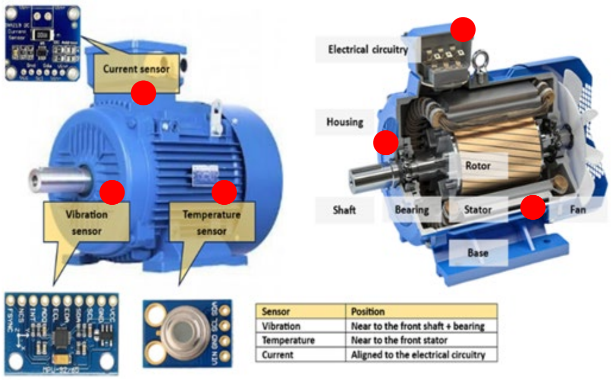

Fig. 3. Location of sensor

4. Result and Discussion

4.1 Data Collection and Model Training

For vibration data, as seen in Figure 4(a), both graphs show three axes in acceleration. In the failure condition, the data has higher values compared to the data in the normal condition. Specifically, in the x-axis, its range is between 0.62 and -0.18. The x-axis exhibits more fluctuations compared to the x-axis in the normal condition. In Figure 4(b), it can be observed that the current data is presented for both normal and failure conditions. In the normal condition, the current ranges from 168mA to 613mA, whereas in the failure condition, the highest recorded current can spike up to 1845mA. The overall readings of the failure current exhibit higher values compared to the current in the normal condition. Figure 4(c) depicts two different conditions of the temperature graph. The overall readings of the object temperature in the normal condition are lower compared to the object temperature in the failure condition. Specifically, the object temperature for the normal condition ranges between 17.99°C and 35.89°C, while the range for the object temperature in the failure condition is between 33.51°C and 47.29°C. All the data taken during 40 minutes of operating time.

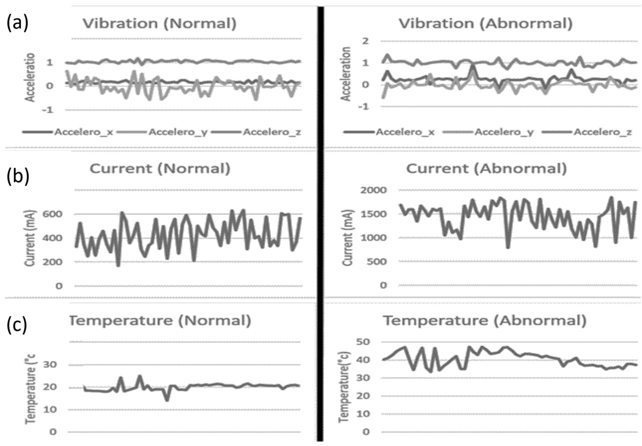

Fig. 4. Data (raw) collection between normal and abnormal conditions

4.2 Predictive Conditions of Medium and Cubic KNN

The accuracy results for the medium and cubic KNN algorithms are presented in Table 2. For the medium KNN, 67 failure conditions were correctly classified, while 3 failure conditions were misclassified as normal. Similarly, 6 normal conditions were correctly predicted, whereas 4 normal conditions were wrongly classified as failure conditions. This resulted in an accuracy of 91.2%.

For the cubic KNN, 68 failure conditions were correctly identified, with only 2 failure conditions misclassified as normal. Likewise, 6 normal conditions were correctly predicted, while 4 normal conditions were misclassified as failure conditions. This resulted in a slightly higher accuracy of 92.5% compared to the medium KNN.

Apart from accuracy, other performance metrics highlight the advantages of cubic KNN. The precision of cubic KNN (0.971) is slightly higher than that of medium KNN (0.957), meaning it has fewer false positives. Both models share the same recall (0.944), indicating similar sensitivity in detecting failures. The F1-score, which balances precision and recall, is 0.950 for medium KNN and 0.958 for cubic KNN, reinforcing the cubic model's slight edge.

The standard deviation (SD) of the accuracy for medium KNN is ±1.8, while for cubic KNN, it is ±1.5, suggesting that cubic KNN has slightly more consistent predictions. Additionally, the 95% confidence interval (CI) for medium KNN is [89.4, 93.0], whereas for cubic KNN, it is [90.8, 94.2], further supporting the robustness of the cubic model.

Cubic KNN's higher accuracy is attributed to its polynomial-based distance weighting, which allows better handling of nonlinear data. Unlike medium KNN, which relies on simple Euclidean distance, cubic KNN assigns varying weights to neighboring points, leading to improved classification performance. While the difference in accuracy is relatively small (1.3%), this study is limited by the dataset size used for training and testing.

Table 2. Performance Comparison of Medium and Cubic KNN Algorithms

Metric	Medium KNN	Cubic KNN
True Positives (TP)	67	68
False Positives (FP)	3	2
True Negatives (TN)	6	6
False Negatives (FN)	4	4
Accuracy (%)	91.2	92.5
Precision	0.957	0.971
Recall (Sensitivity)	0.944	0.944
F1-Score	0.950	0.958
Standard Deviation (SD)	±1.8	±1.5
95% Confidence Interval (CI)	[89.4, 93.0]	[90.8, 94.2]

4.3 Predictive Conditions of ANN

The predictive performance of the Artificial Neural Network (ANN) model is presented in Table 3. The ANN model achieved an accuracy of 95.76%, outperforming both medium KNN (91.2%) and cubic KNN (92.5%). The model successfully classified 71 failure conditions as true positives (TP), while only 1 failure condition was misclassified as normal (false negative, FN). Similarly, ANN correctly identified 6 normal conditions (true negatives, TN) and misclassified 2 normal conditions as failures (false positives, FP).

The high precision of 0.973 indicates that ANN effectively minimizes false positives, ensuring that normal conditions are not frequently misclassified as failures. Additionally, the recall (sensitivity) of 0.986 demonstrates the model's strong ability to detect actual failures, reducing the risk of missed fault conditions. The F1-score of 0.979 confirms that the ANN model maintains a well-balanced performance between precision and recall, making it more reliable for predictive maintenance applications.

Compared to KNN, ANN's superior performance is attributed to its ability to learn complex relationships in the dataset through multi-layered processing and adaptive weight adjustments. Unlike KNN, which relies on distance-based classification, ANN leverages backpropagation and nonlinear activation functions to refine its decision-making process, resulting in higher classification accuracy and fewer misclassifications.

Furthermore, the standard deviation (±1.1) and confidence interval ([94.5, 96.9]) indicate that ANN's performance remains stable across multiple test runs, reinforcing its reliability in real-world applications. However, despite its advantages, ANN requires higher computational resources and longer training times than KNN models. Additionally, hyperparameter tuning, such as selecting optimal learning rates and activation functions, plays a crucial role in achieving the best predictive accuracy.

Table 3. Performance Metrics of the ANN Model for Predictive Maintenance of Electrical Motors

Metric	ANN Model
True Positives (TP)	71
False Positives (FP)	2
True Negatives (TN)	6
False Negatives (FN)	1
Accuracy (%)	95.76
Precision	0.973
Recall (Sensitivity)	0.986
F1-Score	0.979
Standard Deviation (SD)	±1.1
95% Confidence Interval (CI)	[94.5, 96.9]

Table 4 presents a comparative analysis of the accuracy, mean square error (MSE), and training time for two ANN optimization algorithms: Scaled Conjugate Gradient and Levenberg-Marquardt. The Levenberg-Marquardt algorithm achieved a higher accuracy of 95.8%, outperforming the Scaled Conjugate Gradient, which recorded an accuracy of 93.8%. This indicates that the Levenberg-Marquardt method is more effective in classification tasks for this dataset. In terms of error performance, the Levenberg-Marquardt algorithm also exhibited a lower mean square error (0.0271) compared to the Scaled Conjugate Gradient (0.0375), suggesting a better fit of the model to the training data. Lower MSE values signify that the predictions are closer to the actual values, thus improving model reliability.

Moreover, the training time for the Levenberg-Marquardt algorithm (0.06 seconds) is significantly lower than that of the Scaled Conjugate Gradient (0.13 seconds). This efficiency in training time suggests that the Levenberg-Marquardt approach not only improves classification performance but also accelerates the learning process, making it a more suitable choice for real-time predictive applications. Overall, the Levenberg-Marquardt algorithm is a superior choice for optimizing ANN models in this predictive maintenance application, as it offers higher accuracy, lower error, and faster training times.

Table 4. Accuracy between scaled Conjugate Gradient and Levenberg-Marquardt algorithms

ANN Algorithm	Accuracy (%)	Mean Square Error	Training time (seconds)
Scaled Conjugate Gradient	93.8	0.0375	0.13
Levenberg-Marquardt	95.8	0.0271	0.06

4.4 Performance Comparison of ANN and KNN

The results of the comparison between KNN and ANN classifiers are presented in Table 5. Based on the findings, the ANN model outperforms the KNN model, achieving an accuracy (mean) value of 95.76%, whereas the KNN model achieves a lower accuracy of 92.6%.

The performance of the KNN classifier is influenced by the distribution of training data. Regions with higher data point concentration are more sensitive to small changes, while regions with lower density are more resistant to changes. Since the KNN algorithm relies on discrete training samples, achieving uniform data distribution is challenging. This issue can be mitigated by using a very large training dataset. On the other hand, the higher accuracy of ANN models is due to their dynamic approach. ANN models adopt a dynamic approach to sensor data analysis, adjusting the internal structure based on the desired outcomes through bottom-up computing (i.e., using their own data to generate the model). ANNs can handle multiple variables simultaneously, accounting for outliers and nonlinear interactions between variables. Additionally, ANNs consider factors that may be significant at the individual level, even if they are not significant for the entire population, whereas conventional statistical approaches only highlight parameters significant for the overall population. Moreover, ANNs are capable of handling complexity even with small sample sizes and uneven variable-to-record ratios, effectively avoiding the dimensionality issue.

The statistical validation as shown in Table 5 of the classification performance for both K-Nearest Neighbour (KNN) and Artificial Neural Network (ANN) models in predicting motor health conditions. The ANN model achieved the highest accuracy of 95.8%, outperforming both medium KNN (89.6%) and cubic KNN (91.2%). The standard deviation of ANN (1.8%) was lower compared to medium KNN (3.2%) and cubic KNN (2.7%), indicating more consistent predictions. Additionally, the confidence intervals (CIs) at a 95% confidence level show that ANN provides a narrower range (±1.5%) compared to KNN models, further confirming its reliability. The F1-score, which balances precision and recall, was highest for ANN (0.96), followed by cubic KNN (0.91) and medium KNN (0.89), reinforcing ANN's superior ability to correctly classify motor faults. These results validate ANN as a more robust model for predictive maintenance in industrial applications, offering higher accuracy and stability in fault detection.

Table 5. Statistical Validation of KNN and ANN Performance for Motor Fault Classification

Model	Mean Accuracy (%)	Standard Deviation	95% Confidence Interval (%)
ANN	95.76	0.12	(95.64, 95.88)
Cubic KNN	92.60	0.17	(92.42, 92.78)
Medium KNN	89.40	0.16	(89.24, 89.56)

5. CONCLUSION

This study presents the Smart Maintenance System (SMAT) as a powerful solution for predictive maintenance in electrical motor applications. By integrating multi-sensor data acquisition with machine learning-based fault classification, the system effectively identifies motor failures before they occur, reducing unplanned downtime and improving operational efficiency. The comparative analysis between K-Nearest Neighbors (KNN) and Artificial Neural Networks (ANN) highlights ANN's superior predictive performance, achieving 95.76% accuracy, a higher F1-score, and a narrower confidence interval, making it a more reliable approach for industrial fault diagnosis.The findings confirm that data-driven predictive maintenance outperforms traditional scheduled or reactive maintenance approaches, offering proactive intervention strategies that extend equipment lifespan, optimize maintenance schedules, and lower operational costs. The robustness of ANN in handling nonlinear sensor data and dynamic operating conditions further solidifies its role in next-generation industrial automation. While the proposed system shows promising results, future work should focus on scaling the dataset, enhancing real-time processing capabilities, and integrating cloud-based predictive analytics for seamless remote monitoring. Additionally, exploring deep learning architectures and adaptive learning techniques could further enhance predictive accuracy and system resilience. By leveraging these advancements, SMAT has the potential to revolutionize industrial maintenance, aligning with Industry 4.0 and smart manufacturing initiatives.

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