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Machine Learning Motor Vibration Monitoring System with a Service Estimation Date

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Abstract. This paper presents machine learning motor vibration with service estimation date. AI and machine learning algorithms are used to evaluate electric motor vibration patterns and predict maintenance and repair needs. Efficiency, downtime, and maintenance and repair schedule optimisation are project goals. Over time, machine learning algorithms analyse electric motor data to identify vibration patterns. This will predict maintenance and repair needs. KNN, CatBoost, and Neural Network were studied. Machine learning algorithms predicted maintenance and repair needs with over 90% accuracy. Algorithms also calculated the service estimation date, improving maintenance and repair scheduling. It improved maintenance and repair programmes, reduced downtime, and increased reliability. An ESP8266 and a vibration sensor to record and send electric motor data to ThingsSpeak, an IoT website that analyses it. Machine learning algorithms is then used to classify the motor vibration to determine the service estimation date. This project taught me how to maintain and repair electric motors using machine learning and AI algorithms.

Keywords: Algorithm, downtime, vibration, motor, estimation time

1. Introduction

Industry 4.0 and sensor technology advancements have made it possible for smart factories to increase output and quality. As a method to reduce downtime and improve operations, predictive maintenance has gained popularity. Edge computing and the Internet of Things (IoT) have become important technologies for data processing and energy efficiency. Early fault detection has improved with the development of monitoring systems, including wireless sensor networks (WSNs). With improvements in data accessibility and deep learning algorithms enabling real-time motor service life prediction, machine learning has become indispensable in the analysis of motor

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vibration. Predictive maintenance's major goal is to identify equipment and component failures before they occur, allowing manufacturing companies to plan maintenance in advance. The potential for data-driven problem diagnostic techniques has increased as a result of smart factories producing enormous volumes of data that are beyond the ability of human technicians to inspect [1-3].

Condition monitoring systems can benefit greatly from the problem detection and motor behaviour prediction capabilities of the potent gradient boosting algorithm CatBoost. While deep learning, a branch of machine learning that uses multiple-layer neural networks for fault detection, is frequently employed, CatBoost has certain particular advantages for handling gathered data and carrying out fault diagnosis tasks. [4,5] Because CatBoost can handle both category and numerical information, it is particularly well suited for analysing the variety of sensor data gathered by condition monitoring systems. In real-world situations where data quality may fluctuate, its robustness in managing missing values and outliers is advantageous. Additionally, CatBoost demonstrates competence in handling unbalanced datasets, which are frequently present in fault diagnosis tasks [6].

2. Literature Review

In manufacturing, maintenance is a crucial element that raises equipment quality and reliability while lowering equipment downtime. Reactive maintenance, preventive maintenance, and predictive maintenance are the three types of maintenance approaches that are used [1, 7, 8]. Reactive Maintenance, sometimes referred to as Run to Failure (R2F), is a straightforward but expensive maintenance technique. It entails fixing the apparatus after a fault or failure, which can result in additional harm to other parts. Preventative Maintenance (PvM) is founded on regularly scheduled maintenance. PvM, on the other hand, does not take into account the real condition or health of the equipment, which can lead to unneeded expenses and corrective actions such the early replacement of healthy components, which causes unwanted downtime [9-10].

2.1. Sensors

No matter what kind of sensor is employed, the stiffer the mounting, the wider the frequency range, and the more accurate the reading. Vibration sensors are often permanently fixed at a particular location in the machine to allow for continuous or online monitoring of the machine's status. The sensor is fastened to the machine by being fitted into a stud [11-13]. In comparison to other mounting techniques, this one not only has the largest frequency response but is also extremely trustworthy and safe.

Accelerometers are trustworthy and durable sensors used to measure vibration or acceleration. They have a wide frequency range, a lightweight design, and high sensitivity [17]. They can, however, be vulnerable to interference from the environment and need electronic integration for velocity and displacement data. Table 1 shows the advantages and disadvantages in comparison with what each respected author chose.

Table 1. Comparison of sensors.

Sensors	Advantages	Disadvantages
Piezoelectric accelerometer[14]	Lightweight, high sensitivity, good frequency, dynamic range	Needs electronic integration to acquire velocity and displacement data, vulnerable to interference from the external environment
MEMS accelerometer[15,16]	Cheaper than piezoelectric sensor, requires low processing power, high sensitivity	Suffers from poor signal-to-noise ratio
Velocity transducer[3]	Can operate without any external device, generally costs less than other sensors	Limited operational frequency range, most velocity transducers are prone to reliability problems at operational frequency of more than 121°C
Displacement sensor[18]	Good sensitivity, simple postprocessing circuit with negligible maintenance	Succeptible to shock, difficult to install

2.2. Machine Learning Methodology Comparison

The problem being solved and the type of data will determine which algorithm is used. A handful of the several machine learning algorithms employed. CatBoost, developed by Prokhorenkova et al. in 2017, this extremely successful machine learning technique has become quite popular in the field of motor or machinery predictive maintenance [19-20]. CatBoostClassifier's innovative "Ordered Boosting" technique enables it to handle categorical variables efficiently. The data preparation process is made simpler by this feature. Random Forest employs bagging to reduce overfitting and tree-type classifiers. NN is composed of several nodes, which are artificial processing neurons with rich connections, coupled to one another in layers to form a network [21]. The intricacy of the network affects training time, which directly impacts the accuracy of the findings. We can see a summarized comparison in table 2.

Table 2. Comparison of ML Methodologies.

Author	Methodologies	Findings
[20]	Proposed the fuzzy logic method to diagnose the operation of rotating machines	The proposed method can easily diagnose the operational status of the rotating system
[22]	Combined the GA, SVM, and EEMD methods to diagnose gear faults	Incorporating the GA to select the parameter of SVM can improve the generalization ability and classification accuracy of the diagnostic system
[21]	Combined the cepstrum analysis and NN method to detect and diagnose gear fault	NN can diagnose gear faults with high accuracy, provided that proper measured data are used
[17]	Applied the kurtosis and SVM method to diagnose roller bearing fault	The accuracy of the proposed method is 93.75% and can be applied even with a limited number of samples

3. Methodology

The development of an IoT-based monitoring system using sensors, an embedded system, machine learning algorithms, and data processing methods is the chapter's main topic.

3.1. Dataset Acquisition & Data Preprocessing

In this study, a machine learning model was trained using data from an industrial motor. The dataset had six separate imbalance faults, misalignment faults, and normal operation along with unbalanced and normal data. To achieve uniform ranges and standardised features, preprocessing the data is essential. In order to prevent overvaluing higher values and keep interpretability, feature scaling is a crucial stage in this process. Dealing with imbalanced data is crucial since it can impair algorithm performance, result in false representations, and produce substandard results [22,23]. One method frequently used to address imbalanced datasets is down sampling. To obtain an even distribution, it entails lowering the samples from the dominant class.

Around 11 models were tested for this dataset mentioned, namely: HistBoosting, LightGBM, Random Forest, Bagging classifier Boosting, NN, KNN, etc. For their accuracy and the highest accuracy model was chosen. Cat Boost Classifier had the highest accuracy compared to the other models. This process of training the model is discussed in this section. Google Colab is the platform used to train the model and the programming language used is Python.

3.2. IoT

The free website ThingSpeak will be used for IoT monitoring. The first step is to register for a ThingSpeak account. The following action is to establish a channel specifically for motor vibration analysis. For the hardware and ThingSpeak to communicate with one another, getting the Channel ID and API key is essential. The API key functions as a secure access token, enabling authorised devices to submit data to the channel, while the Channel ID operates as a unique identification for the channel.

3.3. Overall System

TheMPU6050 accelorometer is used to collect data from the motor. Data collection and transmission where the nodeMCU receives data from the sensors and delivers it to the cloud after preprocessing. Using ThingSpeak which can handle the volume and variety of data generated by IoT devices. To gain insights into the behavior of the object being watched, the sensor data is processed and visualized. Machine learning techniques, in our case CatBoost and others are being used in this case to find patterns and abnormalities in the data.

3.4. Algorithms Selection

At this point in the investigation, we are mostly concerned with evaluating the accuracy of several machine learning models and looking at their individual ROC scores. The Decision Tree Classifier, Random Forest Classifier, Gaussian NB, K-Nearest Neighbours Classifier, and Gradient Boosting Classifier are a few of the models we first implemented. The confusion matrix, classification report, accuracy, and ROC score are used to assess their performance. We can gauge the model's ability to correctly predict the labels for the motor vibration patterns using the accuracy metric. The model's capacity to distinguish between several classes is also measured by the ROC score, which also accounts for the true positive rate and false positive rate. Better overall performance in differentiating between various vibration patterns is indicated by a higher ROC score as shown in figure 1.

It's crucial to remember that choosing the optimal model might not be just based on accuracy and ROC score. It is also important to consider factors like model complexity, computing needs, and interpretability.

	ROC
CAT Boosting	0.892526
HistBoosting	0.888527
Light GBM	0.886223
Random Forest	0.882578
Bagging Classifier	0.850124
GB Boosting	0.849155
Neural Network	0.823484
Knn	0.817556
ADA Boost	0.800333
DecisionTreeClassifier	0.753919
NB	0.668598

Figure 1. ROC scores comparison.

```
M1=DecisionTreeClassifier()
M1.fit(X_train,y_train)
P1=M1.predict(X_test)
print('confusion_matrix:',confusion_matrix(y_test,P1))
print("\n")
print('classification_repor:',classification_report(y_test,P1))
print("\n")
print('Accuracy:',100*accuracy_score(y_test,P1))
print("\n")
print('ROC:',roc_auc_score(y_test,M1.predict_proba(X_test), multi_class='ovr'))

confusion_matrix: [[ 9132  4762  1359]
 [ 4964  9128  1314]
 [ 1531  1389 12321]]

classification_repor:               precision    recall  f1-score   support

           1       0.58      0.60      0.59     15253
           2       0.60      0.59      0.59     15406
           3       0.82      0.81      0.82     15241

    accuracy                           0.67     45900
   macro avg       0.67      0.67      0.67     45900
weighted avg       0.67      0.67      0.67     45900


Accuracy: 66.62527233115469

ROC: 0.7549612777506117
```

Figure 2. DecisionTreeClassifier Model.

3.5. Different Models and Accuracy

The "DecisionTreeClassifier" class is used in this instance as shown in the figure 2 to construct the decision tree classifier. This model's accuracy, measured as the proportion of cases accurately predicted, is 66.625%. The model's capacity to distinguish between several classes is measured by the ROC score of 0.7549612777506117, where a higher value denotes better performance.

In this instance, the random forest model outperforms the decision tree classifier with an accuracy of 71.45% and a ROC score of 0.882. KNN model with a k value of 2 is constructed using the "KNeighborsClassifier" class. The KNN model's accuracy, measured as a percentage of instances accurately predicted, is 66.61%. The model performs rather well in class separation, according to the ROC score of 0.817. We initialise the CatBoost classifier as M8 and train it on the training data (X_train and y_train). The labels for the test data (X_test) are predicted using the trained model, and the confusion matrix, classification report, accuracy, and ROC score are then computed. The CatBoost classifier excels at correctly categorising the motor vibration patterns, as evidenced by the attained accuracy of 89.5% and the ROC score of 0.89.

4. Results and Discussion

In this section, we present the results and analysis of the service estimation date prediction models for the induction motor fault detection system. We evaluated multiple classification algorithms, including HistBoosting, KNN, NN, and CatBoost Classifier, on various load conditions, namely No Load, 5g Load, 10g Load, and 15g Load

As seen in figure 3, the "No Load" condition, the motor operates without any external load. During this condition, the vibration pattern analysis provides valuable insights into the motor's health and performance. Based on the analysis of the vibration data, an estimated service date of 9 months is recommended. This means that after 9 months of operation under no load, it is advised to conduct maintenance checks and inspections on the motor.

The 9-month estimated service date takes into account the specific vibration patterns exhibited by the motor under no load condition. It indicates that over time, certain wear and tear may occur, internal components may experience degradation, and potential faults or issues may arise. It is essential to emphasize that the estimated service date of 9 months is based on the analysis performed using machine learning models trained on the vibration data collected during the "No Load" condition. However, it is important to consider other factors such as the motor's age, environmental conditions, and historical performance data when determining the actual service date. Regular monitoring, analysis, and refinement of the predictive models will further enhance the accuracy of the service estimation for motors operating under the no load condition.

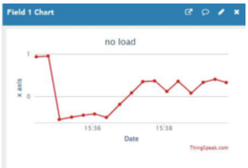

Figure 3. No Load Vibration Pattern.

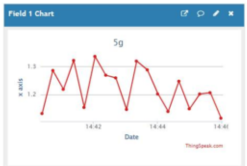

Figure 4. 5g Load Vibration Pattern.

As seen in figure 4, the "5g Load" condition, the motor operates with a load of 5g, which refers to a specific level of mechanical imbalance. This condition introduces additional stress and vibration to the motor. Based on the analysis of the vibration data collected during the 5g load condition, an estimated service date of 6 months is recommended. The 6-month estimated service date takes into account the unique vibration patterns exhibited by the motor under the 5g load condition. The increased load and imbalance put additional strain on the motor's components, potentially accelerating wear and tear. It is important to note that the estimated service date of 6 months is derived from the analysis performed using machine learning models trained on vibration data collected during the 5g load condition. However, it is crucial to consider other factors such as the motor's age, operating conditions, and historical performance data to determine the actual service date accurately. Regular monitoring and refinement of the predictive models will further enhance the accuracy of the service estimation for motors operating under the 5g load condition.

5. Conclusion

The machine learning-based motor vibration monitoring system with a service estimation date, in conclusion, has promise, but there are also drawbacks that must be recognised. The calibre and representativeness of the dataset used for training and evaluation determine the precision and generalizability of the predictions. Performance might be improved by incorporating a more varied dataset with a wider variety of load conditions and fault scenarios. Consistent and accurate sensor readings are required because sensor variability, such as placement, sensitivity, and calibration, can affect the accuracy of vibration data collected. This study's models might behave differently when used with various motor systems, operating situations, or fault types, highlighting the need for additional validation on a variety of datasets. Despite these drawbacks, the technology has the potential to significantly impact society by increasing safety, lowering costs, and improving equipment reliability. Additionally, it supports the SDGs for affordable and clean energy, business and innovation, and sustainable cities and communities. Future suggestions include boosting fault detection capabilities, incorporating real-time monitoring and IoT platforms, and enhancing general equipment performance through preventative maintenance techniques.

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