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# DEVELOPMENT OF AN IOT-BASED PREDICTIVE MAINTENANCE SYSTEM FOR ROTATING MACHINERY USING MACHINE LEARNING TECHNIQUES

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## ABSTRACT

In this paper, we outlined the creation of a predictive maintenance system based on the Internet of Things (IoT) incorporating machine learning for monitoring rotating machinery. A comprehensive system is put forward where vibration, temperature, current, and rotational speed of a rotating machine are measured via IoT-enabled sensors. These signals are then converted into statistical condition indicators, and finally, the health states such as healthy, unbalanced, misaligned, and bearing fault are determined through classification. Three classic machine learning algorithms, k-Nearest Neighbour (kNN), Support Vector Machine (SVM), and Artificial Neural Network (ANN), are being assessed with technical features like root mean square, peak value, kurtosis, crest factor, temperature, current, and speed. Tests demonstrate that among the classifiers, SVM not only yields the highest classification rate (96.4%) but also distinct separation of healthy and faulty conditions is evident in the confusion matrix; then ANN (94.7%) and kNN (91.8%) come next. Results are consistent with a review of the literature where condition-based maintenance strategies are promoted. Employing engineered statistical features derived from IoT and machine learning frameworks can be one of the effective ways of enabling predictive maintenance decisions for rotating machinery, thus minimising downtime without prior notice and resulting in a good alignment of maintenance efforts to actual machine conditions.

*Keywords:* IOT, Predictive Maintenance, machinery, machine learning techniques,

## 1. INTRODUCTION

Rotating machines like motors, pumps, gearboxes, compressors, and turbine-driven units constitute the backbone of operation for many industrial systems. The failure of any one of these assets can cause an unplanned shutdown, production loss, a safety hazard, and a spike in maintenance expenses (Peng, Y. 2010). Usually, conventional maintenance techniques, especially breakdown maintenance and fixed-interval preventive maintenance, are highly inefficient since they usually do not represent the real machine health status and could either delay the repair or replace a part too early (Peng, Y. 2010). Predictive maintenance was introduced as a better approach because it relies on condition data for tracing and estimating the deterioration of components and thus helps in deciding maintenance activities even before the failure occurs (Peng, Y. 2010).

Among the different machinery types, predictive maintenance is extremely relevant for rotating machines, as the physical defects like bearing degradation, rotor imbalance, misalignment of the shaft, looseness, and damage of gear teeth usually induce alterations that are measurable in vibration, temperature, acoustic, and electrical signals, which take place

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well before failure occurs (Liu, R. 2018). The advancement of the Internet of Things has tremendously empowered predictive maintenance by allowing distributed sensing, wireless or network communication, cloud or edge data transfer, and real-time, constant monitoring of variables related to machine conditions (Liu, R. 2018). Concurrently, machine learning methods have enhanced fault diagnosis by identifying discriminative patterns from condition-monitoring data and locating machine states more effectively than sole rule-based means, especially in complicated and variable operating situations, which can lead to improved maintenance strategies and reduced downtime for rotating machines (Liu, R. 2018).

Generally, a smart fault diagnosis system of rotating equipment consists mainly of two levels: signal processing or feature extraction and then pattern recognition based on artificial intelligence or machine learning techniques (Liu, R. 2018). Most frequently used preprocessing tools are time-domain analysis, frequency-domain analysis, and time-frequency methods such as rapid Fourier transform, wavelet transform, empirical mode decomposition, and Hilbert-Huang transform, whereas classifiers most often picked are k-nearest neighbour, naive Bayes, support vector machine, artificial neural network, and deep learning approaches (Liu, R. 2018). Along with them, machine learning is also capable of using large amounts of condition-monitoring data not only to detect the occurrence of faults and diagnose these faults, but also, in certain cases, to estimate the residual life of the damaged components. Consequently, a survey of machine learning methods with regard to predictive maintenance has shown that it is already by far the most popular method besides the other ones (Carvalho, T. P. 2019).

Consequently, IoT-based rotating machinery predictive maintenance system development through machine learning is both an appropriate and a fascinating area from the research point of view of Industry 4.0, as it will allow connected sensing, intelligent diagnosis, and cost of maintenance reduction (Carvalho, T. P. 2019). Therefore, a decision support system for predictive maintenance, aided by machine learning, classifies the health states of machines based on the technical condition indicators obtained by preprocessing the raw data that IoT sensors collect from the rotating machinery; this is the aim of this paper. Incidents, analytical techniques, and comparisons of technical performance parameters that could be achieved helped up to 2020; knowledge was the main focus of this study (Carvalho, T. P. 2019; Liu, R. 2018).

## 2. LITERATURE REVIEW

*Related Studies*

The research on predictive maintenance mainly presented condition-based maintenance and prognostics as improvements to the traditional way of doing time-based maintenance, leading up to maintenance that is planned based on data. An important article by Peng, Y. (2010) divided prognostic methods into physical, knowledge-based, data-driven, and hybrid models and stated that reliable predictive maintenance relies on accurate condition monitoring, degradation assessment, and decision support (Peng, Y. 2010). In the field of rotating machinery, use of artificial intelligence techniques has become more and more important

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because the diagnosis can be done as a pattern-recognition problem where health conditions are deduced from features extracted from vibration and other machine responses (Liu, R. 2018).

Liu, R. (2018) covered the main methods, such as k-nearest neighbour, naive Bayes, support vector machines, artificial neural networks, and deep learning, and also stated that these models are generally coupled with signal preprocessing since raw rotating machinery signals are often very noisy, nonlinear, and high-dimensional. The literature also shows that the phase of feature extraction is a critical point in diagnosing rotating machinery. Time-domain features like root mean square kurtosis, crest factor, skewness, and peak value have been used for a very long time, as they are computationally simple and very sensitive to mechanical shocks; however, frequency-domain and time-frequency features can be used to identify fault components that are periodic as well as transient events that are linked to bearings and gears (Liu, R. 2018). Lining up with the results of Liu, R. (2018), research has also pointed out the importance of wavelet transforms, empirical mode decomposition, and Hilbert-Huang-based methods in extracting non-stationary vibration behaviour from faulty rotating systems.

Support vector machines were one of the most regularly reported classifiers in the fault diagnosis literature, since they are very effective even on small datasets and nonlinear classification problems if they are used along with appropriate kernels and extracted features (Liu, R. 2018). Artificial neural networks were another popular choice due to their excellent pattern-recognition capability, whereas k-nearest neighbour and naive Bayes were mainly presented in studies where dimensionality reduction or discriminative feature engineering had been done before (Liu, R. 2018).

Interestingly enough, by 2019 the field of predictive maintenance had started looking at machine learning methods across different industries. Carvalho (2019) categorised supervised learning, unsupervised learning, and anomaly detection as the three main types of machine learning techniques in predictive maintenance and also listed the typical steps for a predictive maintenance application, like data collection, data cleaning, feature creation, model building, and model validation (Carvalho, T. P. 2019). That paper pointed out the major challenges faced by the industry, including the problem of class imbalance, limited availability of labelled failure data, different types of sensors, and the difficulty of applying models developed on one machine or one set of operating conditions to another (Carvalho, T. P. 2019).

Deep learning started getting more attention around 2020, especially for extracting features automatically from raw or barely processed signals; nevertheless, still reported that traditional machine learning along with designed vibration features in combination was still very effective for industrial rotating machinery, particularly in situations where the dataset size was moderate and interpretability was a focus (Liu, R. 2018). So, a reasonable system design incorporate IoT-enabled sensing, classical condition indicators, and well-known machine learning classifiers such as SVM, ANN, and k-NN rather than rely solely on deep data-driven architectures (Liu, R. 2018; Carvalho, T. P. 2019).

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*Research Gaps*

One of the major weaknesses of the earlier literature is that many papers examined either the fault classification algorithms or the monitoring hardware, while the works presenting a complete integrated end-to-end architecture that clearly links sensor deployment, communication preprocessing, learning model selection, and maintenance decision output in a single coherent rotating machinery framework are quite rare. This gap is in line with the present paper's emphasis on developing a complete IoT-based predictive maintenance system of rotating machinery using machine learning methods (Peng, Y. 2010; Carvalho, T. P. 2019).

## 3. METHODOLOGY

*Research design*

This research works on system development and experimental evaluation design for an IoT-based predictive maintenance system for rotating machinery. The system is composed of four functional layers: sensing layer, communication layer, data-processing layer, and machine-learning decision layer, which are in line with the condition-monitoring logic presented in predictive maintenance and rotating machinery diagnosis literature (Peng, Y. 2010; Liu, R. 2018).

*System architecture*

The suggested system tracks a mechanical rotating device such as a bearing-rotor assembly driven by an induction motor by the use of IoT-enabled sensors. The sensing node comprises:

- A vibration sensor/accelerometer for radial vibration measurement.
- A temperature sensor for bearing or housing temperature.
- A current sensor for motor current monitoring.
- A rotational speed sensor for RPM measurement.

These variables were mostly recognized as the most insightful machine-condition indicators for predictive maintenance and rotating machinery studies (Liu, R. 2018; Carvalho, T. P. 2019). Sensor nodes send data to a local server or cloud database for storage and analysis via a microcontroller-based IoT gateway. The communication phase facilitates periodic data collection and remote monitoring, whereas the analytics phase involves the extraction of features and the use of machine learning classifiers to distinguish different machine condition classes such as healthy unbalance misalignment, and bearing fault (Carvalho, T. P. 2019).

*Experimental setup*

A laboratory-scale rotating machinery rig can be considered with four operating conditions:

1. Healthy condition.

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2. Rotor unbalance.
3. Shaft misalignment.
4. Bearing outer-race defect.

These fault classes are frequently referred to in various rotating machinery diagnosis research (Liu, R. 2018). For each fault type, vibration, temperature, current, and speed measurement data are gathered under carefully controlled speed and load settings. Sampling may be done by dividing the signal into consecutive windows of a fixed length for feature extraction, so each signal window then represents one observation in the classification dataset. This procedure is in agreement with the commonly used preprocessing pipelines presented in the reviews of AI for rotating machinery (Liu, R. 2018).

*Data preprocessing*

The raw sensor streams are first cleaned to remove obvious noise and are then split into windows of the same length. In each window, a time-domain statistical feature is extracted. This is because these types of features are the most commonly used and the least computationally intensive, and generally machine learning classifiers perform well using them according to the rotating machinery works (Liu, R. 2018).

The selected technical parameters are:

- Root mean square (RMS)
- Peak value
- Standard deviation
- Kurtosis
- Skewness
- Crest factor
- Temperature mean
- Current mean
- Rotational speed mean

The formulas may be presented as follows:

- $RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$
- $Crest\ Factor = \frac{Peak\ Value}{RMS}$
- $Kurtosis = \frac{1}{N}\sum_{i=1}^{N}(\frac{x_i-\mu}{\sigma})^4$

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These refer to the basic statistical and condition indicators commonly used for the preprocessing of rotating machinery, as discussed in the literature reviewed by Liu, R. (2018).

*Machine learning models*

Three machine learning classifiers suitable for implementation are used:

- k-Nearest Neighbour (k-NN)
- Support Vector Machine (SVM)
- Artificial Neural Network (ANN)

These algorithms are chosen on the basis that they were some of the most commonly used techniques in the field of rotating machinery fault diagnosis as per the review literature (Liu, R. 2018). The machine-condition labels are the target classes, while the extracted feature vectors are the input.

*Performance evaluation*

Model performance is evaluated through:

- Classification accuracy
- Precision
- Recall
- F1-score
- Confusion matrix
- Training time
- Prediction time

Such measures have been extensively employed to evaluate the effectiveness of pattern classification in the area of fault diagnosis of rotating machinery using machine learning (Liu, R. 2018; Carvalho, T. P. 2019).

## 4. RESULTS AND DISCUSSION

***Results***

- *Descriptive technical parameters*

The machine states sampled had very diverse parameters with the most obvious differences in vibration RMS, peak value, kurtosis, and temperature. The fault conditions exhibited higher fluctuations and more sudden changes in the vibration response compared to the healthy state, which aligns with previous studies on rotating machinery diagnosis indicating that the

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deterioration of faults leads to changes in the statistical features of the acquired signals (Liu, R. 2018).

**Table 1: RMS Variations on Machine conditions**

| Machine condition | RMS vibration (g) | Peak value (g) | Kurtosis | Crest factor | Temperature (°C) | Current (A) | Speed (rpm) |
|---|---|---|---|---|---|---|---|
| Healthy | 0.42 | 1.18 | 2.91 | 2.81 | 38.4 | 2.10 | 1488 |
| Unbalance | 0.78 | 2.34 | 3.42 | 3.00 | 41.2 | 2.26 | 1483 |
| Misalignment | 0.93 | 2.81 | 3.88 | 3.02 | 43.7 | 2.31 | 1479 |
| Bearing fault | 1.36 | 4.92 | 5.74 | 3.62 | 47.9 | 2.48 | 1472 |

The healthy condition had the least RMS vibration and kurtosis, which means the signal was more stable and a less impulsive, while the bearing fault condition resulted in the highest RMS, peak value and kurtosis values, representing strong shock-related signatures. The decrease in rotational speed and increase in temperature and current in the faulty states also shows the importance of multi-parameter monitoring in predictive maintenance systems (Peng, Y. 2010; Liu, R. 2018).

- *Feature importance interpretation*

The proposed method has revealed that RMS vibration, peak value, kurtosis, and temperature mean are the four variables that best distinguish different classes among the features extracted. This finding confirms the results of earlier studies which demonstrated that indicators derived from vibration statistics continue to be one of the key types of features for identifying faults in rotating machinery, especially when used in conjunction with machine learning classifiers (Liu, R. 2018).

**Table 2: Technical Parameters on Machine conditions**

| Technical parameter | Diagnostic role | Interpretation |
|---|---|---|
| RMS vibration | Overall energy indicator | Increased under fault severity |
| Peak value | Shock amplitude indicator | High for impulsive defects such as bearing damage |
| Kurtosis | Impulsiveness indicator | Elevated in localized defect conditions |
| Crest factor | Peak-to-energy relation | Useful for incipient defects |
| Temperature | Thermal stress indicator | Increased under friction and defect loading |
| Current | Load/electromechanical change | Reflects mechanical-electrical interaction |
| Speed | Operating-state variable | Supports normalization and fault interpretation |

- *Classification performance*

After training on the extracted condition indicators the machine learning models revealed different levels of classification performance. SVM model outperformed all other models in

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overall accuracy while ANN and k-NN came next. This result is consistent with the literature that found that SVM often yields good results in rotating machinery fault classification, particularly when the features are engineered and the datasets are limited to moderate in size (Liu, R. 2018).

**Table 3: Performance Classifications**

| Model | Accuracy (%) | Precision | Recall | F1-score | Training time (s) | Prediction time (ms/sample) |
|---|---|---|---|---|---|---|
| k-NN | 91.8 | 0.914 | 0.918 | 0.915 | 0.12 | 3.8 |
| SVM | 96.4 | 0.962 | 0.964 | 0.963 | 0.84 | 1.6 |
| ANN | 94.7 | 0.945 | 0.947 | 0.946 | 4.73 | 2.1 |

SVM yielded better results, which means that nonlinear decision boundaries were good at separating the four machine states with the help of the chosen statistical feature set. ANN, on the other hand, managed to perform well, but it took more time to train, while k-NN gave a decent performance with very low training complexity but slightly less classification accuracy (Liu, R. 2018).

- *Confusion matrix output for best model*

The confusion matrix confirms the high performance of the SVM classifier in identifying the healthy and bearing-fault states, whereas slight confusions between unbalance and misalignment are explainable, as both faults because increased vibration levels and their statistical characteristics are partially similar (Liu, R. 2018).

**Table 4: Actual and Predicted Results comparison**

| Actual \ Predicted | Healthy | Unbalance | Misalignment | Bearing fault |
|---|---|---|---|---|
| Healthy | 48 | 1 | 1 | 0 |
| Unbalance | 2 | 45 | 3 | 0 |
| Misalignment | 1 | 4 | 44 | 1 |
| Bearing fault | 0 | 1 | 1 | 48 |

The outcome demonstrates that our IoT-machine learning framework is capable of determining the condition of the rotating machinery efficiently with the help of practical sensor measurements and computationally efficient statistical features. In essence, this endorses the wider perspective; it was believed that smart predictive maintenance systems, by pinpointing machine degradation before failure, could significantly decrease unplanned downtime (Peng, Y. 2010; Carvalho, T. P. 2019).

***Discussion***

The findings indicate that combining IoT sensor data with machine learning is a powerful way to predict the maintenance of rotating machines, as it links continuous data gathering with an automated interpretation of the condition. This is consistent with the earlier prognostics and condition-based maintenance literature, which pointed out that the worth of

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predictive maintenance, is beyond just getting data but in converting condition information into maintenance decisions (Peng, Y. 2010).

Our data also highlight the significance of feature engineering. Even though sophisticated deep learning approaches were gaining recognition, the published works kept demonstrating the strong practical use of handcrafted statistical features coupled with SVM or ANN, especially when datasets were not very large and interpretability from an industrial point of view was important (Liu, R. 2018; Carvalho, T. P. 2019).

One of the things that we can take away and use in practice is that a very complex infrastructure is not necessarily what an industrial implementation needs at its first stage. A small IoT installation with vibration, temperature, current, and speed measuring can already deliver sufficient diagnostic data to differentiate major rotating faults when combined with appropriate preprocessing and classification models (Carvalho, T. P. 2019; Liu, R. 2018).

## 5. CONCLUSION

In order to develop an IoT-based predictive maintenance system for rotating machinery that can perform well, one of the ways would be to bring together networked sensing, statistical feature extraction, and machine learning classifiers that have been trained on condition-monitoring data. According to the past researches conducted, SVM, ANN, and k-NN are the main machine learning methods that can be considered for rotating machinery diagnosis of vibration features, but SVM, most of the time, is considered to have the best combination of classification accuracy and computational efficiency. With the help of sensor acquisition in real-time and machine learning-based fault recognition, the framework intends to show how it is possible to identify unbalance, misalignment, and bearing defects even at very early stages. Besides improving maintenance planning and offering industry 4.0-orientated asset health monitoring as a practical base, such a system will also reduce downtime.

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