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Developing Algorithm for Fault Detection and Classification for DC Motor Using Predictive Maintenance

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Abstract - *Maximizing production quantity and quality while retaining the lowest possible production and maintenance costs is the primary goal of an industrial facility or utility. This can only be accomplished if the plant operates effectively; hence, regular maintenance is required. There are numerous tactics, but industry 4.0 predictive maintenance is among the most important. Predictive maintenance assists in foreseeing faults that will happen following data processing and alerts the operator. Predictive maintenance technology increases the efficiency of plant maintenance, lowers maintenance costs, and extends the useful life of the equipment. This study examines the design and development of the predictive maintenance algorithm for anticipating both healthy and defective data from real-time data from DC Motor Hardware*

Key Words: Predictive Maintenance, DC Motor, Industry 4.0, Tree, MATLAB

1.INTRODUCTION

Since the early days of the industrial revolution, maintenance has been primarily reactive, responding to equipment breakdowns, resulting in unexpected downtime and high maintenance costs. However, with technological advancements, maintenance practises have become more advanced and proactive. Nowadays, maintenance tasks are performed proactively based on predetermined schedules and utilise modern monitoring and diagnostic tools [1]. The least ideal option is reactive maintenance, which includes repairing equipment after it has failed. Preventive maintenance, on the other hand, is performing routine maintenance to avoid breakdowns. Predictive maintenance uses advanced monitoring technology to detect possible equipment breakdowns, allowing maintenance work to be scheduled ahead of time. Industrial organisations may ensure that their equipment functions at maximum capacity by selecting the optimal maintenance technique, resulting in greater productivity and reduced downtime.

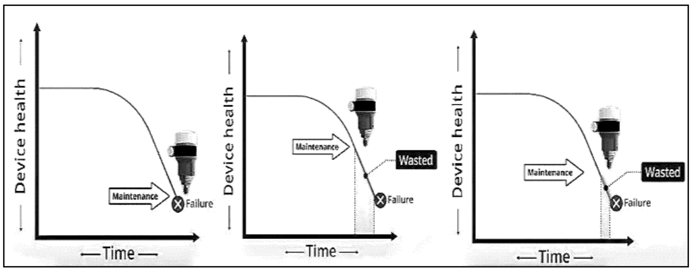


Figure 1: Types of Maintenance (Ref: RealPars)

The least ideal option is reactive maintenance, which entails repairing equipment after it has failed. Preventive maintenance, on the other hand, is performing routine maintenance in order to avoid breakdowns. Predictive maintenance makes use of modern monitoring technologies to predict possible equipment breakdowns, allowing maintenance work to be scheduled ahead of time. Industrial organisations may ensure that their equipment functions at maximum capacity by selecting the appropriate maintenance strategy, resulting in greater productivity and reduced downtime.

Predictive maintenance is important in Industry 4.0, the fourth industrial revolution marked by the incorporation of digital technologies into industrial processes show in fig 2 [2]. To optimise industrial processes, massive amounts of data from sensors and other sources are collected and analysed in Industry 4.0. In this context, predictive maintenance combines contemporary sensors and analytical technologies to monitor system status and forecast repair needs in real time. This preventive strategy decreases the likelihood of accidental interruption. One of the benefits of predictive maintenance in Industry 4.0 is the possibility of shifting from reactive to proactive maintenance operations. Manufacturers can reduce operating expenses, boost equipment efficiency, and improve total output by estimating future failures.

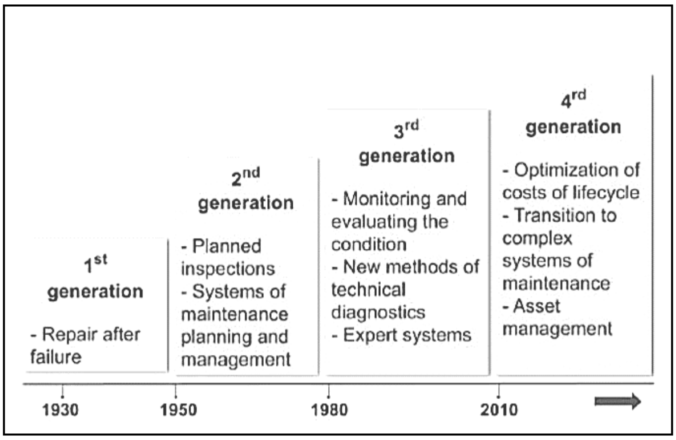


Figure 2: Evolution of Maintenance (Ref: 2)

Predictive maintenance methods are classified into three types: data-driven, model-based, and hybrid approaches [3]. Machine learning and statistical approaches are used in data-driven ways to estimate equipment failures and maintenance requirements based on data from multiple sources. Model-based approaches use physics-based models to simulate equipment behaviour and predict maintenance requirements under various operating situations. To provide more precise and dependable estimates of equipment performance and maintenance requirements, hybrid systems combine data-driven and model-based methodologies.

There are many additional predictive maintenance technologies available, such as vibration analysis using the Fast Fourier transform [4], predicting power system health through ageing mechanisms [5], and locating hot areas in transformers using thermal imaging [6]. Predictive maintenance can also be accomplished by anomaly identification based on thermodynamic equations for compressor discharge temperature [7], neural network analysis of data patterns [8], and root cause analysis to determine the underlying causes of equipment failures [9].

Predictive maintenance solutions based on prognostics and health management (PHM) and condition-based maintenance (CBM) methodologies are critical tools for industries, especially in this age of rapidly evolving information and communication technologies (ICTs) [10]. These strategies help firms manage maintenance more effectively and reduce expenses by recognising possible problems early on [11]. The notion of the Online System for Condition Monitoring and Maintenance (OSA-CBM) is a critical industry standard that allows for the early detection of maintenance issues through online data analysis [12]. Industries can avoid equipment failures by embracing this modern technology.

2. ARCHITECTURE OF PDM.

A predictive maintenance system's standard structure involves several stages. The data acquisition layer enables sensors and other devices to acquire operational data from the equipment. The obtained data is pre-processed and filtered in the data preparation layer to verify its quality. The machine learning layer then enters the picture, where algorithms are trained to detect patterns and anomalies in the data. Finally, the maintenance execution layer is in charge of doing any necessary repairs or replacements. This architecture enables organizations to proactively discover and repair equipment faults, avoiding costly downtime and lowering maintenance costs. As shown in fig 3

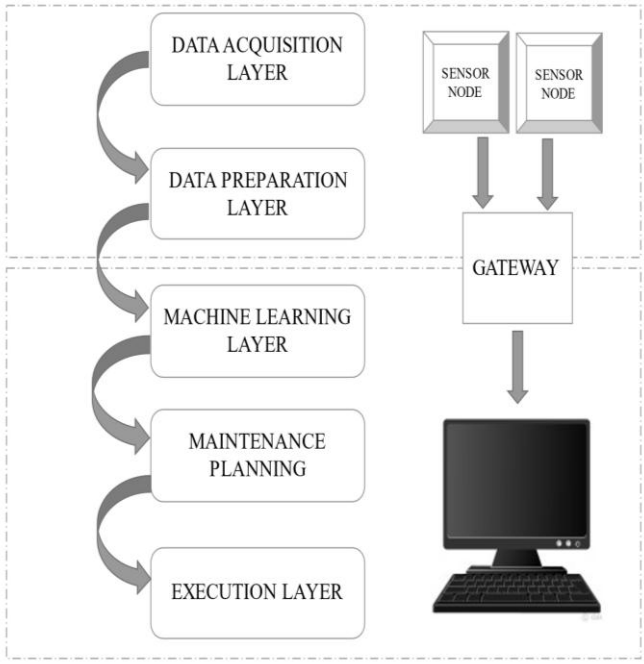


Figure 3: Architecture of PdM

3. PREDICTIVE MAINTENANCE ALGORITHM.

A set of instructions used by a computer to solve a problem or complete a task is known as an algorithm. It is a set of well-defined rules used in computer algorithms for a number of objectives including data analysis, machine learning, and optimization. Advanced data analytics are used by predictive maintenance algorithms to predict equipment faults and maintenance requirements. These algorithms look for patterns and anomalies in historical and real-time data. Predictive maintenance algorithms help minimize costly breakdowns and enhance equipment reliability by proactively recognizing possible concerns. In Predictive Maintenance Algorithm there are main six steps. They are as follows:

Step 1: The initial step is to collect data from diverse sources, such as sensors, machines, and systems.

Step 2: The gathered data is then pre-processed to remove any irrelevant or noisy data and to convert it into an analysis-ready format.

Step 3: From the pre-processed data, features related to the maintenance work are extracted.

Step 4: Using the retrieved features, a predictive model is created that can detect anomalies and anticipate equipment breakdowns.

Step 5: To ensure accuracy and reliability, the created model is validated using historical or test data.

Step 6: The final step is to put the predictive model into a real-time production environment where it can monitor the equipment and send out maintenance notifications.

4. IMPLEMENTATION OF PDM.

A. DC Motor Hardware System

The DC motor hardware system is a complicated arrangement that incorporates components such as a Hall effect sensor, NTC thermistor, piezoelectric sensor, Arduino Uno, and L298N controller IC. All of these components develop a example of closed-loop system that collects data such as temperature, vibration, RPM, ADC temperature, and thermistor resistance. This system is an illustration of the cooling system.

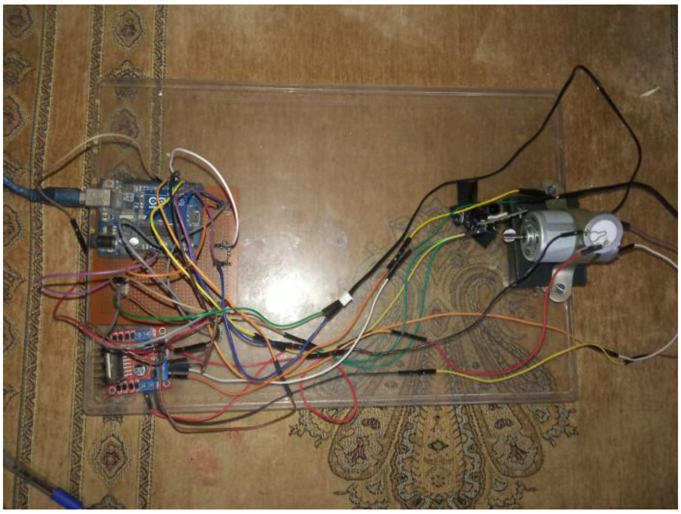


Figure 4: Hardware (1)

The Hall effect sensor detects the magnetic field of the motor, allowing it to calculate the RPM and monitor performance. The NTC thermistor serves as a temperature sensor, monitoring heat levels to ensure safe operating temperatures. The piezoelectric sensor detects vibrations, which aid in the diagnosis of mechanical faults or imbalances. The Arduino Uno serves as the control center, gathering and processing sensor data with the ADC. Based on the information received, the L298N driver IC regulates the motor's speed and direction.

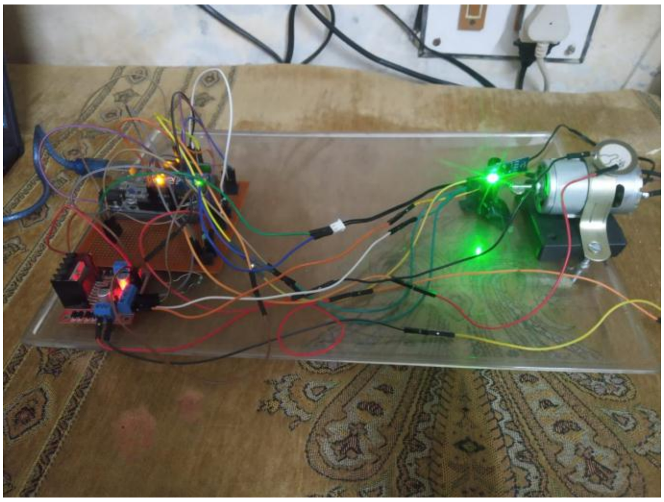


Figure 5: Hardware (2)

Once all of these components are combined, a comprehensive monitoring and control setup is created, exemplifying a cooling system. It monitors vibrations and offers vital data on RPM and thermistor resistance while ensuring optimal motor operation within temperature limits. This technology improves motor performance, extends its lifespan, and guards against future failures.

B. DATA COLLECTION

The hardware system is effortlessly linked to a computer using a USB port. The Arduino code is loaded into the Arduino IDE software. The code is for gathering real-time data from the close loop hardware system, and five features are collected from the sensors linked to the system. Temperature, vibration, speed, ADC temperature, and thermocouple resistance are the five features. A condition is set for operating the motor so that if the temperature exceeds the required value, the motor will start working. There is also a requirement for motor speed, such that the motor should operate at the desired value. For that PID Controller is used in Arduino code. If the motor is overloaded, it will indicate "faulty" and "healthy" So, the last column of data consists of a class of data, whether it is working in a healthy condition or a faulty condition. These data are collected in the CSV file for further processing.

C. DATA PROCESSING

In this section, the data gathered from the DC motor hardware is processed using a machine learning method. We used MATLAB to create the predictive maintenance fault detection and classification Programme. MATLAB features a predictive maintenance toolbox that includes the Diagnostic Feature Designer tool and the Classification Learner application. The Diagnostic Feature Designer tool is used to extract the features, and the Classification Learner application is used to train data using multiple machine learning models. After gathering enough data to execute a machine learning technique, the data is used in classification learner software to train various types of machine learning algorithms. 70% of the data is used for training and 30% for testing, with five points of cross-validation. Further the data is trained for all available machine learning models. The model with the high accuracy and minimum time to train is selected and the trained model is then exported for the testing purpose. The machine learning model's accuracy and time is mentioned in the below table.

Table 1: Observation Table

ML Model	Accuracy	Prediction Speed	Time/secs
Tree	100%	~19000 obs/secs	9.3
Naïve Bayes	46.8%	~64000 obs/secs	1.9135
SVM	61.1%	~99000 obs/secs	33.273
KNN	99.2%	~11000 obs/secs	13.432

After Training the data in the Classification Learner App. We adopted the Decision Tree (DT) machine learning model for training since it provides higher accuracy, more observation per seconds and takes less time to train the model than other machine learning algorithms. Scatter Plot is obtained for Tree. As shown in fig 6

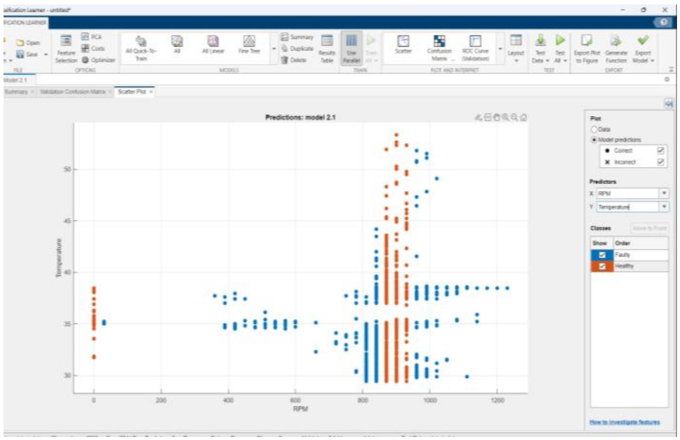


Figure 6: Scatter Plot Trained Data

It is observable that the data collected from the Hardware system can be easily interpreted. In Scatter Plot the Blue describes the Faulty data and Orange describes Healthy data. For plotting the scatter plot two variables are used Temperature and Speed. The X-Axis represent the Temperature and Y-Axis represents RPM. A confusion Matrix is also obtained for the trained data. As shown in fig 7.

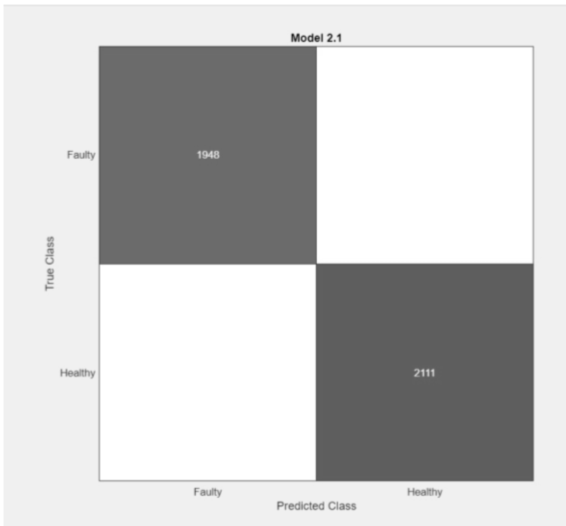
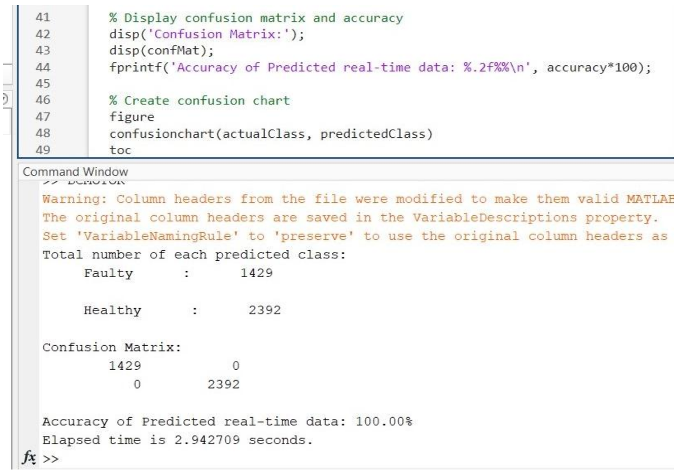


Figure 7: Confusion Chart Trained Data

Next, the trained model is exported to MATLAB for the further experiment. The trained model is used to classify the real time data which we have collected after deploying the DC Motor Hardware System. The real time data is collected from the close loop system for testing purpose. The data is stored into excel file which is used to predict and classify the data.

D. RESULTS

The results are show in the command which states the number of predicted values of each class and also gives the exact numbers of healthy and faulty data. It also generated the confusion matrix for the testing data and Scatter Plot for New Test Data after prediction is made. The accuracy of prediction is >95%. As shown in fig 8,9,10.



```
% Display confusion matrix and accuracy
disp('Confusion Matrix:');
disp(confMat);
fprintf('Accuracy of Predicted real-time data: %.2f%%\n', accuracy*100);

% Create confusion chart
figure
confusionchart(actualClass, predictedClass)
toc
```

```
Command Window
Warning: Column headers from the file were modified to make them valid MATLAE
The original column headers are saved in the VariableDescriptions property.
Set 'VariableNamingRule' to 'preserve' to use the original column headers as
Total number of each predicted class:
     Faulty     :     1429

     Healthy     :     2392

Confusion Matrix:
        1429           0
           0        2392

Accuracy of Predicted real-time data: 100.00%
Elapsed time is 2.942709 seconds.
fx >>
```

Figure 8: Test Data Results

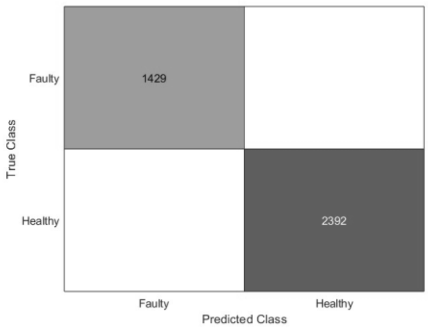


Figure 9: Test Confusion Matrix

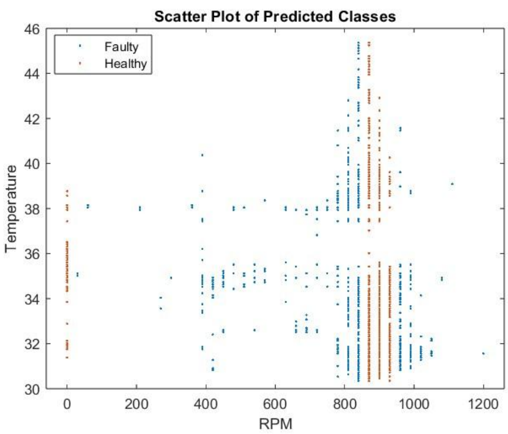


Figure 10: Test Scatter Plot

5. CONCLUSIONS

In conclusion, using decision trees in MATLAB's Classification Learner App offers a convenient and efficient method for correctly identifying and categorizing faults in DC motors. Industries can change their maintenance procedures to improve performance, reduce costs, and increase operational efficiency by utilizing decision trees' adaptability. Decision trees' interpretability promotes educated decision-making, proactive maintenance, and downtime minimization. All things considered, decision trees provide a strong method to enhance the performance and dependability of DC motors in many industries.

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