Predictive Maintenance of Induction Motor in the Cutting Section of Paper Industry

KALAVATHIDEVI T, MADHAN MOHAN M, BALUPRTHVIRAJ K N,
SANGAVI B, RAJARAGHAVENDRAA S K, RAJESHKANNA K
Electronics and Instrumentation Engineering
Kongu Engineering College
Perundurai, INDIA

Abstract: - Induction Motors are vital to the paper industry because they power a variety of equipment needed for pulp processing, drying and cutting among other tasks. Ensuring the consistent manufacture of these motors and satisfying market demands depends heavily on their dependability. However, the extreme humidity, dust and fluctuating loads that occur in the paper sector present serious obstacles to the efficiency and durability of induction motors. To maintain continuous production and satisfy consumer demand, the paper industry significantly depends on the effective operation of a variety of machinery including induction motors in the cutting area. Unexpected malfunctions in these vital parts however might result in expensive downtime and lost output. By using data-driven strategies that anticipate and avoid breakdowns before they happen, predictive maintenance techniques provide a proactive way to reduce such risks. This report provides an extensive analysis of the application of predictive maintenance techniques designed especially for induction motors in the paper industry's cutting division. The predictive maintenance techniques includes Random Forest Tree, Linear Regression and Support Vector Machines algorithm with these algorithm the Induction Motor's variations in temperature, vibration, sound, and speed parameters were collected and trained for predicting the failure. Among these algorithms Support Vector Machines shows greater advantage in predicting the failure with the accuracy of 84% whereas Random Forest Tree with 75% and Linear regression with 72%. As well as the real time data's were collected and stored in the database. The performance of the Induction Motor were efficiently improved and monitored under normal and fault condition by Machine Learning techniques.

Key-Words: -Induction Motors, Sensing Data, Downtime, Motor Failure Prediction, Random Forest Tree, Linear Regression, Support Vector Machines
Received: March 6, 2024. Revised: August 24, 2024. Accepted: September 18, 2024. Published: October 15, 2024.

1. Introduction

In the paper industry, the quality of the finished product is largely determined by the cutting section. This section's machinery is powered by induction motors, however because of their proneness to wear and tear they can have unplanned breakdowns and expensive downtime. Predictive maintenance uses machine learning algorithms to anticipate possible breakdowns in advance providing a proactive way to reduce these risks [1]. Machine reliability is crucial during this crucial stage of production in order to maintain manufacturing processes and satisfy strict quality standards. Induction Motors which precisely and effectively drive the cutting tools are among the vital parts that power these machines [5].However, a number of variables, such as environmental considerations, mechanical loads, and wear and tear can affect how well Induction Motors operate in the cutting area. Unexpected failures or breakdowns in these motors can result in expensive production downtime, lower output, and lowered product quality [6]. As a result, maintaining the competitiveness and profitability of paper production operations depends critically on the induction motor's dependability and optimal performance. Predictive maintenance offers a proactive solution by utilizing cutting-edge technologies and data-driven insights to anticipate and prevent failures before they occur [9].

Predictive maintenance systems can identify early indications of deterioration or approaching failures by continuously monitoring motor performance characteristics like temperature, vibration, sound, speed and current [4]. Predictive maintenance also optimizes maintenance schedules, lowers unscheduled downtime and lowers overall maintenance costs in addition to improving equipment reliability [3]. This study is to investigate the benefits, methods and guiding principles of predictive maintenance with a focus on induction motors used in the paper industry's cutting division.
The primary objectives of this research are:

1.To implement the predictive maintenance for Induction Motors in the cutting section of the paper industry is to minimize unplanned downtime.
2.To optimize maintenance costs associated with Induction Motors in the cutting section.
3.To extend the lifespan of Induction Motors in the cutting section of the paper industry by identifying and addressing potential issues early on.
Harsh operating environments, complex dynamics, data availability issues and integration hurdles with traditional maintenance practices pose significant obstacles. Overcoming these challenges is essential for enhancing equipment reliability, minimizing downtime and optimizing maintenance costs to ensure operational efficiency and competitiveness in the market. This is the problem statement given by the Seshasayee Paper and Boards Ltd (SPB). To overcome the existing problem, we came over an idea of predicting the failures in advance by collecting the data from the induction motor via sensors. Implementing predictive maintenance involves deploying sensor systems to monitor Induction Motor parameters such as temperature, vibration, sound, and speed. Data is collected and analyzed using machine learning algorithms to detect anomalies indicating potential failures. This method optimizes maintenance practices in the paper industry's cutting section enhancing equipment reliability and efficiency.

2. Literature Survey

An Artificial Intelligence based fault detection system was proposed by Marichal et al. This work examined the vibration properties of a water-based oil separation system. In order to forecast the early stages of failures, the vibration signals were first processed in the frequency domain and then applied to a genetic neuro fuzzy system [7]. The issue of using power signals and a genetic algorithm to optimize Support Vector Machines (SVMs) is addressed in order to create an optimal classification model for electric motor defect diagnostics. When fault diagnostics is used an electric motor's operating status can be quickly identified, and a response is made to increase the motor's reliability [2]. A real-time monitoring system with preventive defect detection alerts were described because it uses big data processing, hybrid prediction models, and Internet of Things-based sensors, this system can efficiently handle and analyze massive volumes of data. In this case, the hybrid prediction model combines the more accurate defect identification of Random Forest classification with noise-based outlier detection. It demonstrated how the suggested paradigm enhanced decision-making and helped avoid unforeseen errors [13]. Analysis is carried for predictive maintenance in aviation, particularly for line maintenance near the gate. It proposes a methodology utilizing prognostics and the extended Kalman filter for optimizing maintenance of redundant aeronautical systems, considering multiple wear conditions. The aim is to enhance aircraft availability and reduce costs, addressing critical aspects of the aviation industry's maintenance challenges [14].

The unexpected downtime of diagnostic and therapeutic imaging systems presents financial issues for hospitals and Original Equipment Manufacturers (OEMs) in the cost-sensitive healthcare business. The suggested methodology makes use of contemporary connectivity to support the connection of equipment to a typical monitoring station, allowing for predictive maintenance and remote monitoring. This proactive strategy reduces unscheduled downtime by foreseeing possible faults and is based on a data-driven, machine learning framework [10]. The recurrent equipment breakdowns and unplanned downtime from reliance on Reactive and Preventive Maintenance at Company X, this paper proposes an Artificial Intelligence (AI)-based model for optimizing current maintenance strategies. Using the Nowlan and Heap risk analysis matrix, critical equipment-pumps, storage tanks, valves, and the standby power supply system was identified at the fuel depot. Ishikawa diagrams were applied to refine the Preventive Maintenance strategy [8]. The integration of vibration sensors into the Internet of Things (IoT) is gaining prominence, driven by advancing technology that enhances measurement accuracy and reduces hardware costs. These sensors, affixed to core equipment in control and manufacturing systems like motors and tubes, offer crucial insights into device operational status. Our data engine focuses on Remaining Usefulness Lifetime (RUL) estimation, crucial for cyber-physical system maintenance, demonstrating on real manufacturing sites a 1.2x extension in tube lifetime and a 20% reduction in replacement costs [3].Process Monitoring and Predictive Maintenance is evident in manufacturing, aiming to cut maintenance costs and minimize downtime. This paper introduces an adaptive Predictive Maintenance based flexible maintenance scheduling decision support system, emphasizing opportunity and risk costs. Validation on a real industrial dataset related to Ion Beam Etching in semiconductor manufacturing demonstrates the system's effectiveness in enhancing maintenance strategies [12]. An experimental approach for integrating

Industry 4.0 into a small bottling plant, specifically focusing on early fault detection in conveyor motors and generate predictive maintenance schedule. Using advanced programming functions of a Siemens S7-1200 PLC, vibration speed data is monitored through sensors, allowing for efficient maintenance planning. Additionally, a decentralized monitoring system facilitates cloud-based reporting and sends immediate email notifications to supervisors for generated maintenance schedules, enhancing the practical implementation of Industry 4.0 in the bottling plant [5].

The significance of condition monitoring and Predictive Maintenance in preventing economic losses due to unforeseen motor failures and improves the system reliability. It introduces a Machine Learning architecture based on the Random Forest approach for predictive maintenance. The system's validation involves a real industry example, incorporating data collection from diverse sensors, PLCs, and communication protocols within the Azure Cloud. [9]. The constant push for reducing operational and maintenance costs of Induction Motors (IMs) underscores the importance of regular system health monitoring. This paper offers a state-of- the-art review on IM faults and diagnostic schemes, addressing the increasing demand for condition monitoring in industrial applications. Various fault diagnosis techniques for IMs are explored; highlighting the potential of non-invasive data acquisition for future dynamic machine maintenance and failure prediction [1].The paper introduces the PdM approach, outlines a PdM scheme for automatic washing equipment and discusses challenges in PdM research. It categorizes industrial applications based on six machine learning and deep learning algorithms, comparing performance metrics for each. The analysis delves into the accuracy of these PdM applications, evaluating algorithm performance in detail [15]. This paper reviews recent advancements in predictive maintenance for motors, highlighting outcomes, ongoing research, and key contributions by researchers, reflecting the growing importance of PdM in ensuring the reliability of electric motors [6]. The analysis categorizes research based on metric capacity unit algorithms, machine learning class, machinery, instrumentation, data acquisition devices, and data size and type. It highlights key contributions by researchers and offers insights for further research. The paper presents a Random Forest model for predicting machine failures in manufacturing, demonstrating its superior accuracy and precision compared to the Decision Tree algorithm [4]. This paper provides an overview of key approaches to bearing-fault analysis in grinding machines. It categorizes these approaches into two main parts: the first involves classifying bearing faults based on detection, error position, and severity, while the second focuses on predicting remaining useful life to optimize replacement costs and minimize downtime [11]. One-class support vector machine (OC-SVM), one of the several boundary-based techniques and algorithms suggested to address this issue, is regarded as particularly good and efficient. However, one major disadvantage of this classifier group is their excessive sensitivity to the presence of noise and outliers in the training data [16].

This paper presents an innovative method for anomaly detection and fault diagnosis featuring online adaptive learning. The method combines classification and clustering, demonstrating superior performance, particularly with limited known fault types. Experimental validation on ball bearing and Iris datasets confirms its effectiveness [17]. An ensemble of hybrid intelligent models is proposed for induction motor condition monitoring. Motor Current Signature Analysis (MCSA) is chosen for its online, non-invasive nature and single input requirement, ensuring cost-effectiveness. The proposed hybrid model combines the Fuzzy Min–Max (FMM) neural network with Random Forest (RF), forming an ensemble of Classification and Regression Trees for improved accuracy and robustness in monitoring [18]. This paper introduces a pattern recognition system for ongoing induction motor monitoring. It utilizes visually efficient invariant features to identify 3-D current state space patterns, enabling automatic fault detection and severity assessment. The system handles time-variant electric currents, focusing on identifying specific patterns in three-phase stator currents. Simulation and experimental results confirm the methodology's effectiveness in continuous monitoring of complex systems [19]. It explains the generation of vibration and noise in bearings, covering measurements in both time and frequency domains. Signal processing techniques like the high-frequency resonance method are discussed. Acoustic measurement methods such as sound pressure, sound intensity, and acoustic emission are reviewed. Recent research trends, including the wavelet transform method and automated data processing, are also examined [20].

3. Block Diagram for implementing Predictive Maintenance of Induction Motor in the cutting section of paper industry

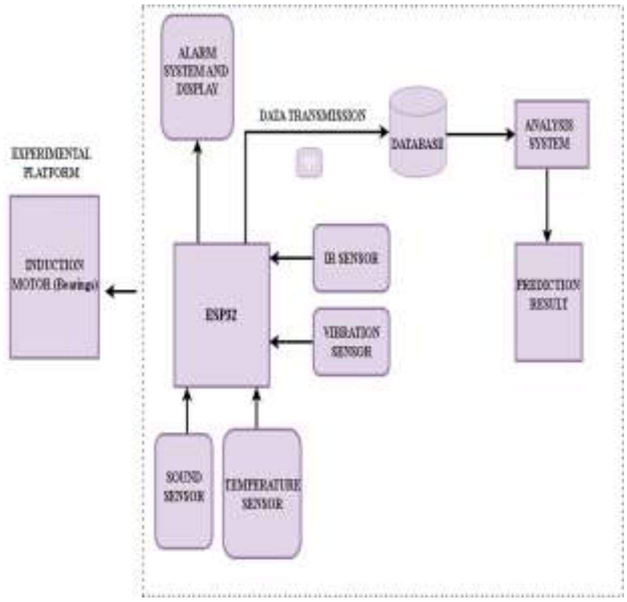

Fig. 1: Block Diagram for implementing Predictive Maintenance of Induction Motor

The block diagram for Predictive Maintenance of Induction Motor in the cutting section of paper industry is depicted in Fig. 1. It consists of a Induction Motor, Sound sensor, Temperature sensor, Vibration Sensor, IR sensor, Alarm system and LCD Display. Various sensors are used to monitor parameters of the induction motor including vibration, temperature, sound and speed sensors. These sensors are connected to ESP32 controller which collects data from the sensor systems and processes it into a usable format. The collected data and real time monitoring data where stored in the database. Then the machine learning models are used to identify patterns, anomalies and potential faults in the motor's operation.Finallythe algorithms predicts the future health condition of the induction motor based on the current data and historical trends.

4. Prototype for Predictive Maintenance of Induction Motor in the cutting section of paper industry

The hardware system for predictive maintenance of induction motors in the paper industry’s cutting section incorporates a variety of sensors including vibration sensor, temperature sensor, speed sensor and sound sensor. These sensors are strategically placed on the motor and surrounding equipment to capture data related to the motor’s operating conditions. The hardware system includes a predictive analytics module that utilizes machine learning algorithms to analyze sensor data and predict potential motor failures. This module continuously learns from historical data to improve accuracy over time. A user interface which is a graphical display provides visualizations of motor health metrics and alerts for detected faults. This interface enables operators and maintenance personnel to make informed decisions. A reliable power supply ensures continuous operation of the hardware components even during power outages.

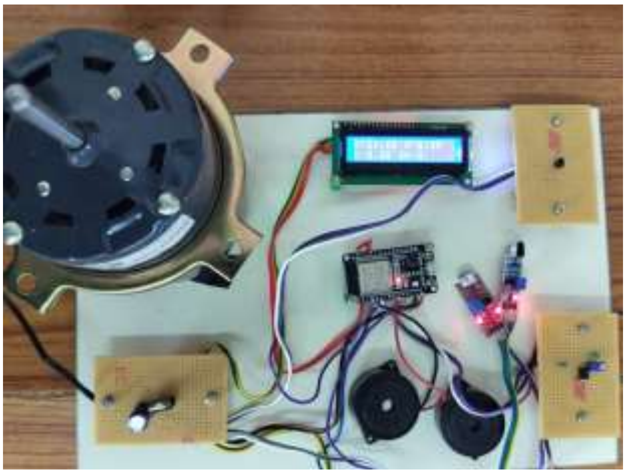

Fig.2: Hardware developed for Predictive Maintenance of Induction Motor

Fig. 2 shows the Prototype of Predictive Maintenance of Induction Motor in the cutting section of paper industry. By integrating these hardware components into a compatible system predictive maintenance of induction motors in the paper industry’s cutting section becomes feasible. The system enables proactive maintenance practices, reduces downtime and enhances overall operational efficiency.

5. Percentage Occurrence of Induction Motor faults

Fig. 3 describes the percentage occurrence of faults in Induction Motors which can vary depending on factors such as operating conditions, maintenance practices and environmental factors. Bearing wear is one of the most common faults in induction motors, accounting for a significant percentage of total faults. The occurrence rate is observed as 69% of all motor faults. Rotor bar and end ring defects such as broken bars or high resistance connections are another prevalent fault in induction motors. Their occurrence rate is typically observed as 7%. Stator winding faults including short circuits, open circuits and insulation degradation are also relatively common in induction motors. Their occurrence rate varies but generally falls within 21%. Shaft misalignment which can occur due to improper installation or mechanical wear is another significant fault in induction motors. Its occurrence rate is typically within 3%. Hence from this it is analyzed that the bearing fault is the major cause for the induction motor failure.

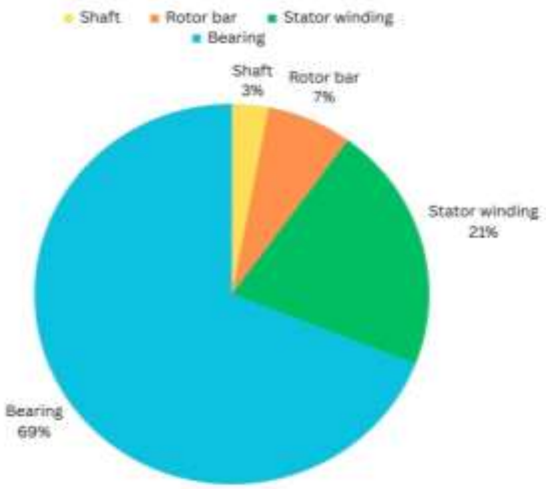

Fig. 3: Percentage occurrence of Induction motor faults

6. Dataset description and Pre-processing

6.1 Gathering Data

This study uses actual data from a local paper firm that supplies hundreds of businesses with paper products as described in Table 1. This article focuses on the examination and forecasting of an Induction motor projection from a paper manufacturer. With an initial sampling interval of two hours, the information in result describes the fundamental parameters of temperature, vibration, speed, and sound utilized by this paper company to describe the operation of its induction motor. To aid in the study of Induction Motors in order to avoid failure and to direct the company's manufacturing. The data's were collected every 240 minutes for 12 days. The time series plot was obtained as shown in Fig. 4.

Table 1. Database obtained from Sensors

S.No	Temperature (°C)	Vibration (m/s^2)	Sound (dB) x10	Speed (RPM) x10
1.	77	4	7	28
2.	49	4	6	86
3.	32	0	5	76
4.	103	5	3	68
5.	90	0	2	143
6.	124	1	5	87
7.	130	2	6	142
8.	99	3	15	92
9.	52	1	8	113
10.	79	1	12	52

6.2 Data Pre-processing

The outlined procedure addresses common challenges encountered in gathered data analysis, encompassing the handling of null values, outliers, time index setup and data normalization.

1. Null and Outlier Management: During data compilation, efforts were made to identify and eliminate null values and outliers. Missing data points were eradicated, and duplicate entries were removed from consideration.
2. Establishing the Time Index: To facilitate time series analysis, it was imperative to convert the data's datetime column into a datetime data type. Consequently, the DataFrame's index was set to the datetime type, with retime chosen as the designated timestamp for data indexing.
3. Normalization Procedure: Normalization was carried out with the objective of enhancingmodel training precision and expediting convergence. The normalization formula, as described in Equation 1, was employed:

$$x_{norm}=x–x_{min}/x_{max}–x_{min} \quad (1)$$

By systematically addressing these steps, the time series data is prepared for subsequent analysis or modeling, ensuring data integrity and suitability for further investigation.

6.3 Data Visualization and analysis

Data input, time series creation, etc. are all included in the visual presentation. Excel files containing the data for 2023 and 2024 must now be exported to a Python environment in order to be displayed as a data frame. A programmable loop is used to import because of the volume of data and the repeated nature of the process. Since the data is only recorded once every minute, down sampling the data is required since the presentation of the data in minutes is both too large and too little. Matplotlib was then used to perform a visual analysis, and Fig. 4 displays the average monthly Induction Motor projection for 2024.

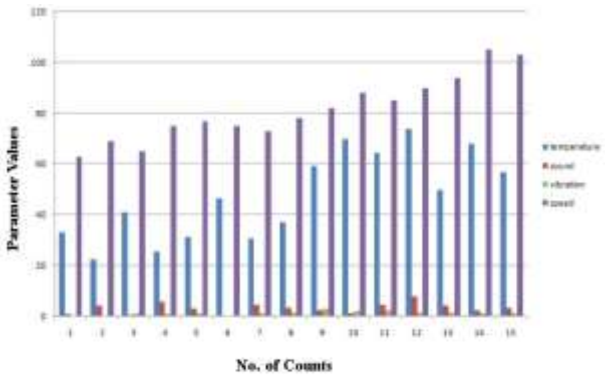

Fig. 4: Average monthly Induction Motor Prediction statics for 2024

7. Induction Motor Prediction

7.1 Random Forest Tree

It can classify different fault types and estimate remaining useful life based on historical data and sensor measurements. The strategy employed here is to achieve these objectives is as follows:

1. Minimizing Individual Error: To ensure low individual error, trees are expanded to their maximum depth.
2. Minimizing Residual Correlation: To reduce residual correlation,
   a) Each tree is grown on a bootstrap sample obtained from the training dataset.
   b) A significantly smaller subset m (where m<<p, p representing the number of covariates) is specified. At each node of every tree, m covariates are randomly selected, and the optimal split for that node is determined based on these selected covariates.

This approach aims to minimize both individual error and residual correlation, thereby improving the model's predictive accuracy and generalization capabilities.

Entropy is measured to check the impurity in a dataset. It's often calculated using the formula,

$H(s) = -\sum_{i=1}^{c} p_i log_2 (p_i)$(2)

where H(S) is the entropy of a set S, c is the number of classes, and p_i is the proportion of instances in class i.

Information gain measures the reduction in entropy or impurity after splitting a dataset on a particular attribute. It's calculated using a formula similar to:

$$IG(D,A) = H(D) - \sum_{V(A)} \frac{|D_V|}{|D|} . H(D_V) \qquad (3)$$

where IG (D,A) represents the information gain achieved by splitting dataset D on attribute A, |D| is the total number of instances in dataset D, $|D_V|$ is the number of instances in dataset D with value V for attribute A, and H(D) and $H(D_V)$ are the entropies of dataset D and its subsets D_V respectively. Fig. 5 shows the block diagram of Random Forest Tree which is a machine learning algorithm commonly effective in analysing sensor data to predict motor failures and schedule maintenance tasks. The Random Forest Tree assesses motor health by monitoring temperature (>85°C), vibration (>2.5 m/s²), sound (>70dB), and speed (<700rpm). Any deviation signals potential failure.

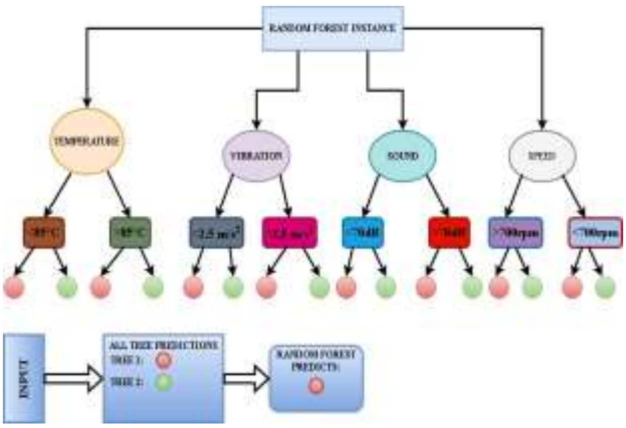

Fig. 5: Block Diagram of Random Forest Tree for Induction Motor Prediction

7.2 Linear Regression

Linear Regression provides the relationship between two variables that is a dependent variable and an independent or explanatory variable. It is used in prediction, forecasting and error reduction. Fig. 6 depicts the relationship between dependent and independent variables.

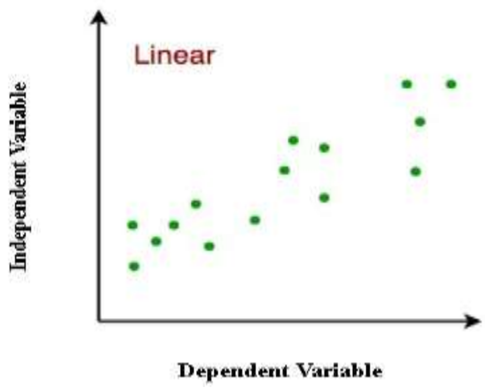

Fig. 6: Relationship between dependent and independent variables

In predictive maintenance of induction motors using linear regression, the one commonly used equation is the linear regression model itself.

$$y=\beta_0+\beta_1 x_1+\beta_2 x_2+\ldots\ldots\ldots\ldots\ldots+\beta_n x_n+\epsilon \quad (4)$$

where, y is the dependent variable (e.g., motor health indicator), x_1, x_2,……..,x_n are the independent variables (e.g., motor operating conditions, environmental factors), β_0+ β_1+………+ β_n are the coefficients representing the relationship between the independent variables and the dependent variable, ϵ represents the error term. In this specific scenario, the dependent variable would likely be a binary outcome indicating whether the motor is in a failure condition or not (e.g., 1 for failure, 0 for non-failure). The independent variables would be the parameters that are believed to influence motor failure, such as temperature, vibration, sound, and speed. If the predicted probability of failure exceeds a certain threshold, the motor would be classified as being in a failure condition. Otherwise, it would be classified as not being in a failure condition.

7.3 Support Vector Machines

Support Vector Machines (SVMs) are a popular algorithm used in predictive maintenance tasks including those related to induction motors. SVMs are primarily used for classification tasks which involve predicting a categorical label based on input features. In the context of predictive maintenance for induction motors, SVMs can be used to classify the health status of the motor (e.g., normal, faulty, impending failure) based on features extracted from sensor data or other relevant sources.

The basic idea of SVM is to find the hyperplane that best separates the data points belonging to different classes while maximizing the margin between the classes. In the case of non-linearly separable data SVM can use a kernel trick to map the input data into a higher-dimensional space where it becomes linearly separable. The features extracted from sensor data exhibit a linear separation between different health states of the motor (e.g., normal, faulty) so that the linear SVM is preferred. For example, if the sensor measurements directly correlate with the health status in a roughly linear manner a linear SVM can provide a simple and effective solution.

The decision function for a linear SVM is proposed as,

$$f(x)=\mathrm{sign}(w.x+b) \quad (5)$$

Where:
x is the input feature vector,
w is the weight vector,
b is the bias term,
sign is the sign function indicating the predicted class.

The weight vector w and bias term b are learned during the training phase.

The objective function of the linear SVM can be formulated as a constrained optimization problem:

$$min_{w,b\frac{1}{2}\|w\|^2} (6)$$

subject to the constraints:

$$y_i(w.x_i+b)\geq 1 \text{ for } i = 1,\ldots..,N \quad (7)$$

where x_i are the training samples, y_i are their corresponding labels (+1 or -1 for binary classification), and N is the number of training samples.

In the case of SVM for predictive maintenance of induction motors, the input features would include various sensor measurements such as temperature, vibration, current, etc., and the output would be the health status of the motor (e.g., normal, faulty). The SVM algorithm would learn to classify the health status based on these features. The SVM model is trained using the pre-processed data. During training, the model learns to distinguish between normal and failure conditions based on the provided features. In this case, the parameters for the SVM model would need to be set to appropriately capture the conditions specified, temperature > 85°C, vibration > 2.5 m/s², sound > 70 dB, and speed < 700 rpm. These parameters would guide the decision boundary of the SVM to classify instances accordingly.

Finally, the trained SVM model can be used to predict the condition of the motor in real-time based on new measurements of temperature, vibration, sound, and speed. If the conditions specified (temperature > 85°C, vibration > 2.5 m/s², sound > 70 dB, and speed < 700 rpm) are not met, the SVM model would predict that the motor is under a failure condition.

8. Experimental Flowchart using the algorithms

Fig. 7 represents the flowchart of Predictive Maintenance of Induction Motor in the cutting section of paper industry. Algorithm for predicting the failure of the induction motor is shown below:

Step 1: Data Collection: Gather data from the induction motor and its environment. This includes motor operating parameters such as temperature, vibration data, speed and sound.

Step 2: Data Preprocessing: Clean the data to remove noise and handle missing values. Normalize the data to ensure consistency and compatibility across different features.
Step 3: Feature Extraction: Extract relevant features from the preprocessed data.
Step 4: Model development: Suitable machine learning models such as Linear regression, Support Vector machine and Random Forest tree models are chosen for parameter prediction.
Step 5: Train the selected models using historical data, with features as inputs and the target variable being either future motor condition or likelihood of failure.
Step 6: Model Evaluation: Validate models using separate test datasets to ensure their effectiveness.
Step 7: Deployment and monitoring: Set up real-time monitoring systems to collect streaming data from the motor. Apply the trained model to make predictions or detect anomalies.
By implementing a predictive maintenance algorithm adapt to the specific needs of the cutting section of the paper industry, businesses can minimize downtime, reduce maintenance costs and optimize the lifespan of critical equipment like Induction Motors.

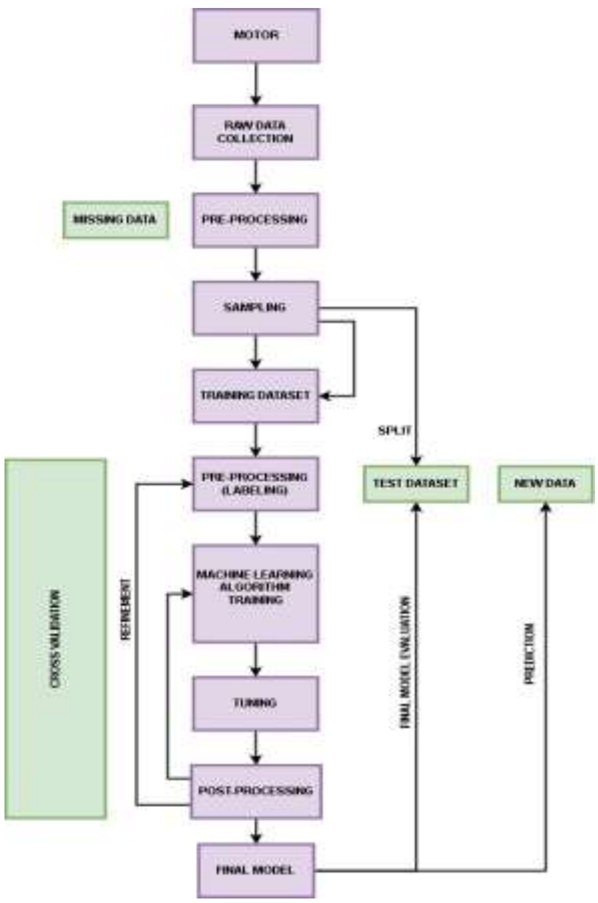

Fig. 7: Flowchart of Predictive Maintenance of Induction Motor

9. Results and Discussion

The trained model by Support Vector Machines algorithm, the outputs are obtained under two conditions,
a)Induction Motor operated under normal condition
b)Induction Motor operated under fault condition

Table 2 shows the Conditions for Temperature, Vibration, Speed and Sound of the motor to determine whether it is under normal state or fault state. If the temperature value exceeds 85°C or Vibration value exceeds 2.5 m/s2 or Sound value exceeds 7dB or Speed value decreases below 70rpm the motor will face failure.

Table 2. Test Set Conditions

Parameters	**Conditions**
Temperature	>85°C
Vibration	>2.5 m/s^2
Sound	>7dB x 10
Speed	<70RPM x 10

a) Induction Motor operated under normal condition

Table 3. Real-time monitored data of normal motor (Without fault)

Temperature (°C)	Sound x10 (dB)	Vibration (m/s^2)	Speed x 10 (RPM)	Motor's Condition
33.23558	0.7820	0	63	NORMAL
22.48289	4.3988	0	69	NORMAL
41.05572	0.6827	1.2736	65	NORMAL
25.41545	5.6696	0.7542	75	NORMAL
31.28055	3.0303	1.2078	77	NORMAL
46.43206	0.4455	0.2234	75	NORMAL
30.79179	4.6920	1.1706	73	NORMAL
37.14565	3.2258	1.5564	78	NORMAL
59.13979	2.3460	2.1804	82	NORMAL
68.91496	1.1730	1.9962	88	NORMAL

Table 3 shows the real-time monitored parameters of the induction motor this includes Temperature, Vibration, Speed and Sound of the motor. Table 3 depicts the real-time monitored data when a motor is operating under normal conditions, without any fault, typically includes a range of parameters and metrics that indicate the health and performance of the motor. For example, in Table 3 Temperature is noted as 33.23558°C, Sound is noted as 0.78201 dB, Vibration is observed as 0 m/s2 and Speed is noted as 63 RPM, all these data were below the test set conditions (Temperature >85°C, Sound >7dB, Vibration >2.5 m/s2 and Speed <70

RPM). From these values it is validated that the motor is operating without any fault.

These data are crucial for ensuring smooth operation and early detection of any potential issues. From the above data the motor failure can be predicted according to the trained dataset. If any of the four parameters fails to achieve the normal value then we can say that the motor is in fault stage otherwise the motor will operate under normal condition. Here there will be no failure occurs since it has no faults in it.

Fig. 8: The Output obtained in ThinkSpeak for Real-time monitored data when motor is operated under normal state (Without fault)

From Fig. 8 it is seen that the motor is operating normally without any fault. When monitoring a motor's operation under normal conditions without any faults, the real-time data displayed on a platform like ThingSpeak provides a comprehensive view of various parameters. For example, in Table 3 Temperature is noted as 25.41545°C, Sound is noted as 5.6696 dB, Vibration is observed as 0.7542 m/s2 and Speed is noted as 75 RPM, all these data were below the test set conditions (Temperature >85°C, Sound >7dB, Vibration >2.5 m/s2 and Speed <70 RPM). These parameters are usually displayed in real-time on a ThingSpeak dashboard or interface, allowing operators to monitor the motor's health and performance remotely. Any deviations from expected values or sudden changes outside normal ranges may trigger alerts or notifications, prompting further investigation or preventive maintenance actions to ensure uninterrupted operation and prevent potential faults or failures.

b)Induction Motor operated under fault condition

Table 4 shows the real-time monitored parameter's of the fault induction motor this includes Temperature, Vibration, Speed and Sound of the motor.

Table 4. Real-time monitored data of fault motor (With fault)

Temperature (°C)	Sound x10 (dB)	Vibration (m/s^2)	Speed x 10 (RPM)	Motor's Condition
60.5368	5.8125	0	90	NORMAL
86.2889	14.698	2.564	70	FAILURE
81.1521	13.264	2.8736	75	FAILURE
85.5145	14.597	3.7542	85	FAILURE
99.8855	13.135	2.2458	75	FAILURE
96.5366	8.1435	2.2734	60	FAILURE
100.8927	14.321	2.4716	80	FAILURE
104.8445	15.139	1.5784	70	FAILURE
109.1969	12.540	2.9847	65	FAILURE
118.9466	11.710	1.9972	50	FAILURE

Table 4 depicts the real-time monitored data of fault motor. Real-time monitored data of a faulted motor provides crucial insights into the abnormal conditions and issues affecting its operation. From the above data the motor failure can be predicted according to the trained dataset. For example, in Table 4 Temperature is noted as 86.2889°C, Sound is noted as 14.6982 dB, Vibration is observed as 2.564 m/s2 and Speed is noted as 70 RPM, all these data were exceeded the test set conditions (Temperature >85°C, Sound >7dB, Vibration >2.5 m/s2 and Speed <70 RPM). From these values it is validated that the motor is facing failure.

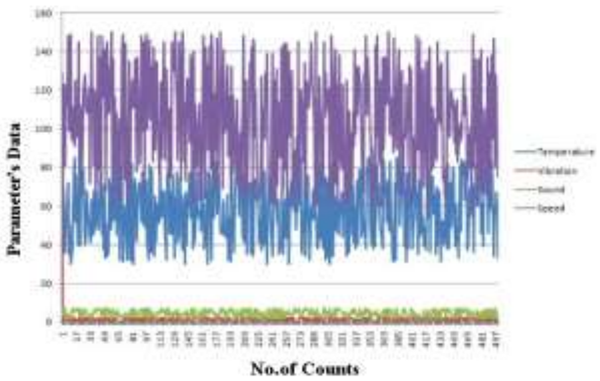

Fig. 9: The Output obtained for Real-time monitored data when motor is operated under fault state (With fault)

Here, the fault occurs due to bearing failure majorly and shaft failure minorly. If any of the four parameters fails to achieve the normal value then we can say that the motor is in fault stage otherwise the motor will operate under normal condition. Fig. 9

depicts the Output obtained for Real-time monitored data when motor is operated under fault state (With fault).

Fig. 9 depicts sudden spikes in the graph that deviate significantly from the expected patterns. In Fig. 9 the glitches is due to the bearing failure and shaft failure. Because of that the Temperature and Vibration varies drastically to the highest point where as the Speed and Sound varies to the lowest point. These anomalies could indicate faults or irregularities in the motor's operation.

Calculating prediction accuracy of Support Vector Machine algorithm is another method for evaluating and comparing classifiers. The values can be obtained from Table 3 and Table 4.

$$Accuracy = \frac{(TP+TN)}{(Total\ Samples)} * 100 \qquad (8)$$

Where TP = Number of true positives instances (TP),
TN = Number of true negatives instances (TN).

The model correctly identifies 12 samples as true positives (failure of motor) and 9 samples as true negative (motor under normal state) out of a total of 25 samples, the accuracy is computed as follows:

Accuracy = (12 + 9) / 25 * 100 = 84%

The accuracy comparison of various Machine Learning algorithms carried out is shown below,
Table 5. Accuracy rate of various algorithms

Model	Random Forest Tree	Linear Regression	Support Vector Machines
Accuracy	75%	72%	84%

Table 5 depicts the accuracy rate of various algorithms, when comparing the accuracy of these algorithms it's essential to consider the specific characteristics of the dataset such as its size, dimensionality, linearity and class distribution. Conducting cross-validation and tuning hyperparameters can help in obtaining more reliable accuracy estimates for each algorithm. Additionally, ensemble methods like Random Forest can sometimes outperform individual models like Linear Regression or SVM particularly in complex datasets with nonlinear relationships.

The performance comparison of various Machine Learning algorithms is depicted below,

Table 6. Performance Comparison among various algorithms

Metrics	Random Forest Tree	Linear Regression	Support Vector Machines
Precision	0.87	0.68	0.92
Recall	0.82	0.75	0.88
F1-Score	0.84	0.71	0.90

Based on the results from Table 6, we can observe that the Support Vector Machines (SVM) algorithm outperforms both Random Forest and Linear Regression in terms of accuracy, precision, recall, and F1-score. SVM achieves the highest values for all these metrics, indicating its superiority in predicting motor failure conditions based on the specified parameters.

10. Conclusion

In conclusion, Predictive Maintenance of Induction Motors in the paper industry's cutting section holds significant promise for improving operational efficiency, reducing downtime and minimizing maintenance costs. By leveraging advanced techniques such as sensor data analysis, machine learning algorithms like Random Forest, Linear Regression, Support Vector Machines and IoT-enabled monitoring systems, predictive maintenance enables early detection of potential faults and proactive intervention before failures occur. Improved Reliability by identifying and addressing potential issues before they escalate into major failures, predictive maintenance enhances the reliability and uptime of induction motors in the cutting section. Cost Savings by Proactive maintenance strategies help minimize unplanned downtime, reduce repair costs and optimize maintenance schedules, resulting in significant cost savings for paper industry operations.

Acknowledgement:
We thank Kongu Engineering College for motivating and encouraging us to do this project in our academic year.

References:

[1] Choudhary A., Goyal D., Shimi S.L. and Akula A., Condition monitoring and fault diagnosis of induction motors, *Archives of Computational Methods in Engineering*, Vol.26, No.4, 2019, pp. 1221-1238.

[2] Gou X., Bian C., Zeng F., Xu Q., Wang W. and Yang S.,A Data-Driven smart fault diagnosis method for electric motor, *IEEE International*

Conference on Software Quality, Reliability and Security Companion, 2018, pp. 250-257.

[3] Jung D., Zhang Z. and Winslett M.,Vibration analysis for IoT enabled predictive maintenance, *International conference on data engineering*, 2022, pp. 1271-1282.

[4] Karrupusamy P., Machine Learning Approach to Predictive Maintenance in Manufacturing Industry, *Journal of Soft Computing Paradigm*, Vol.02, No.4, 2020, pp. 246-255.

[5] Kiangala K.S. and Wang Z.,Initiating predictive maintenance for a conveyor motor in a bottling plant using industry 4.0 concepts, *The International Journal of Advanced Manufacturing Technology*, Vol. 97, 2023, pp.3251-3271.

[6] Manjare A.A. and Patil B.G.,Condition based techniques and predictive maintenance for motor.*International Conference on Artificial Intelligence and Smart Systems*, 2021, pp. 807-813.

[7] Marichal G.N., Avila D., Hernandez A., Padron I. and Castejon C.,Feature extraction from indirect monitoring in marine oil separation systems,*Sensors*, Vol. 18, No. 9, 2018, pp.3159.

[8] Mushiri T., Hungwe R. and Mbohwa C.,An artificial intelligencebased model for implementation in the petroleum storage industry to optimize maintenance, *International Conference on Industrial Engineering and Engineering Management*, 2021, pp. 1485-1489.

[9] Paolanti M., Romeo L., Felicetti A., Mancini A., Frontoni E. and Loncarski J.,Machine learning approach for predictive maintenance in industry 4.0., *International Conference on Mechatronic and Embedded Systems and Applications*, 2020, pp. 1-6.

[10] Patil R.B., Patil M.A., Ravi V. and Naik S.,Predictive modeling for corrective maintenance of imaging devices from machine logs, *International Conference of the IEEE Engineering in Medicine and Biology Society*, 2019, pp. 1676-1679.

[11] Schwendemann S., Amjad Z. and Sikora A.,A survey of machine-learning techniques for condition monitoring and predictive maintenance of bearings in grinding machines, *Computers in Industry*, Vol. 125, 2021, pp.103380.

[12] Susto G.A., Wan J., Pampuri S., Zanon M., Johnston A.B., Hara P.G. and McLoone S.,An adaptive machine learning decision system for flexible predictive maintenance,*International Conference on Automation Science and Engineering*, 2019, pp.18–22.

[13] Syafrudin M., Alfian G., Fitriyani N.L. and Rhee J.,Performance analysis of IoT-based sensor, big data processing, and machine learning model for real-time monitoring system in automotive manufacturing,*Sensors*, Vol. 18, No. 9, 2018, pp.2946.

[14] Vianna W.O.L. and Yoneyama T.,Predictive maintenance optimization for aircraft redundant systems subjected to multiple wear profiles,*IEEE Systems Journal*, Vol. 12, No. 2, 2020, pp.1170-1181.

[15] Weiting Zhang, Dong Yang and Hongchao Wang,Data-Driven Methods for Predictive Maintenance of Industrial Equipment,*IEEE Systems Journal*, Vol. 13, No. 3, 2022, pp. 2213-2227.

[16] Tian Y, Mirzabagheri M, Bamakan S.M.H, Wang H. and Qu Q.,Ramp loss one-class support vector machine; a robust and effective approach to anomaly detection problems, *Neurocomputing*, Vol. 310, 2018, pp.223-235.

[17] Dong L.I., Shulin L.I.U. and Zhang H.,A method of anomaly detection and fault diagnosis with online adaptive learning under small training samples, *Pattern Recognition*, Vol. 64, 2017, pp.374-385.

[18] Seera M., Lim C.P., Nahavandi S. and Loo C.K.,Condition monitoring of induction motors: A review and an application of an ensemble of hybrid intelligent models,*Expert Systems with Applications*, Vol. 41, No. 10, 2019, pp.4891-4903.

[19] Martins J.F., Pires V.F. and Amaral T.,Induction motor fault detection and diagnosis using a current state space pattern recognition, *Pattern Recognition Letters*, Vol. 32, No. 2, 2020, pp.321-328.

[20] Tandon N. and Choudhury A.,A review of vibration and acoustic measurement methods for the detection of defects in rolling element bearings, *Tribology International*, Vol. 32, No. 8, 2017, pp.469-480.

Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

The authors equally contributed in the present research, at all stages from the formulation of the problem to the final findings and solution.

Sources of Funding for Research Presented in a Scientific Article or Scientific Article Itself

No funding was received for conducting this study.

Conflict of Interest

The authors have no conflicts of interest to declare that are relevant to the content of this article.