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DIAGNOSIS AND CONDITION MONITORING OF ELECTRICAL MACHINES USING MACHINE LEARNING TECHNIQUES

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Abstract**—**The simplest components of the electrical industry and power systems are electrical machines such as motors, generators, and transformers, which can lead to life-threatening interference and even economic damage when they are not planned to be used. To address this challenge, machine learning (ML) methods have emerged as effective diagnostics methods of fault diagnosis, and condition monitoring. It is in this paper that systematic analysis will be provided regarding the use of ML algorithms in the process of identifying, classifying, and predicting machine faults through online vibration, temperature, and current measurements. The proposed methodology takes into consideration the endogenous data pre-processing, feature extraction and supervised learning models such as Support Vector Machine (SVM), Random Forest (RF) and Artificial Neural Networks (ANN) to identify faults efficiently. But

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realistic conditions like information asymmetry, limit to sensor location and computational expenses in real time are at stake. Specifically, the future research directions involve the combination of edge-AI structures, federation learning of distributed systems and federation of hybrid deep learning models to provide scaled, adaptive and energy efficient fault diagnosis to conceive Industry 5.0.

Keywords— Machine Learning, Condition Monitoring, Electrical Machines, Fault Diagnosis, Predictive Maintenance, Data-Driven Systems, Vibration Analysis.

I. Introduction

Automated industries, transportation and energy systems are largely dependent on electrical machines such as induction motor, synchronous and generators. Nevertheless, due to the mechanical wear, ageing of insulation and operating stress like machines, they become prone to various kinds of faults (bearing failures, rotor imbalance, stator winding short circuited, misalignment etc.) that may cause early failure of the machine unless they are corrected before it becomes late. Maintenance, Procedures like reactive and preventive maintenance cannot predict such a sort of failures and resultants are lost production, limited equipment life and safety hazards. Hereby, condition-based monitoring (CBM) is becoming more effective in maintenance paradigm whereby the machines are continuously monitored in real-time, and the outcomes of such measurements are taken to determine the well-being of the machines as well as predict the fault, before devastating failures happen [16].

The sophistication of the electric machines has increased and the quantity of the information generated based on the sensors has been of exorbitant kind; this has resulted in the extreme need of the advanced diagnostic system that is able to sustain the non-linearity dependence of the time varying. It can be resolved with the assistance of machine learning (ML) that proposes a data purposeful solution with an algorithm capable of learning regarding the prior data, recognize subtle patterns and forecast the dynamics of the malfunction [3]. The specified change can be aligned with the general shift towards Industry 4.0 paradigm in which predictive maintenance, smart manufacturing processes involving artificial intelligence and Internet of Things (IoT) are shifting to the fully-automated functionality and zero down-time.

The gap that exists between the conventional condition monitoring engines and the smart and data-driven fault diagnosis engines brought about this study. In spite of the fact that, Fast FTP (FFT), Wavelet Transform (WT) and Empirical Mode Decomposition (EMD) signal processing solutions were already heavily relied on in the features extraction domain, they are subject to the limitations of the handcrafted parameters that characterizes the sensitivity of the tools to the different speed of speed and load conditions as relatively restrictive. The later can be resolved with the assistance of the machine learning due to the automatic solmization of discriminative quality of the raw data and generalization to a range of types of errors. Therefore, the purpose of the paper is to develop a complete ML-based fault diagnostic system that can connect the faults of electrical machines with a decent amount of accuracy that can result in something that can maintain the transient operational/ dynamic behavior of the machine [11].

The goals of this research are four:

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- To develop automated fault diagnosis system of electrical machines based on machine learning techniques by using real-time vibration, current and temperature information.
- Introducing different machine learning (Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN)) classifications to compare the diagnostic performance of the different fault conditions.
- Therefore, we have conducted simulation in order to prove the practical feasibility and adaptability of the suggested system in the face of dynamic load, varying environmental condition, etc.

Moreover, certain practical considerations including data imbalance, sensor reliability and computational efficiency are also discussed in this work that are imperative in answering the question of whether the involved systems of ML can be practically implemented in industrial usages. The authors provide the hybridization of the supervised learning and domain knowledge of electrical machine dynamics in the research to reach goals of good interpretability and resistance to fullest extent. Consequently, its objective extends beyond one of a high classification genre, to also provide a generalizable technique to predictive maintenance applications, to machine types that are domain different to one another [12].

In a more general perspective, the applicability of machine learning in condition monitoring systems brings serious consequences to both the operational sustainability and cost efficiency. Machine learning-based predictive maintenance can assist in minimizing maintenance expenses by 30 percent due to unsuccessful equipment failure and extended life of equipment [1]. Moreover, intelligent systems can by means of IoT-enabled architectures offer remote and dynamic tracking of objects in distributed industrial systems that allow maintaining object-specific attributes remote and incessant and under control. Nevertheless, despite all these advantages, it is still a pain to provide the models that are trained under one set of conditions and use them within new settings. Thus, the current study will be useful both scientifically and concerning industries with its ability to design a scalable and adaptable ML-based fault detection framework that is fit enough to be implemented into the real-life situation.

The paper is organized in the following way: Related Study, reported the work done and findings the research gap; Methodology, proposed machine learning framework and datasets design; Results and Discussion, compared performances and discussed what implications it can have in practice; Conclusion, identified major findings and limitations and future research [14-15].

Novelty and Contribution

The originality of the research can be carried on with the combined and adaptive machine learning framework of diagnosis and monitoring of electrical machine under the real-time operating condition. Though fault diagnosis is one of the fields of research through which ML was used, the majority of the research remains to be restricted by data sets generated in a controlled environment or limited expressions of faults. It will go beyond a system of data-driven intelligence and incorporate data-driven intelligence and real world flexibility to solve key industrial problems along with dynamic load variance, noise distortion, and sparse data.

- First, the proposed method offers a hybridization of data preprocessing through time domain, frequency domain, statistical parameters, and so on to obtain enhanced signal representation. The redundancy is minimized by using advanced methods including Principal Component Analysis (PCA) and feature normalization, which result in increasing the diagnostic value of the system. This not only contributes to the computation process being more efficient, but also to the fact that the emphasis on the majority of the discriminative fault features of the ML models.
- Second, the paper is aimed at comparative model testing of SVM, random forest, and ANN architecture to identify the suitable decision of the algorithm to use in the classification of fault depending on various environment conditions. It is specially that ANN model learns the system with a greater flexibility of learning complex, nonlinear relations between sensor measurements and fault states to improve our fast and accurate fault diagnosis system. Such comparative knowledge can be quite helpful to the engineers who want to use the most suitable ML technique in designing some machines.
- Thirdly, the real-time surveillance capabilities are also constructed within the system by simulating the fault detection on the-line and at low latency. This means that the framework can be implemented in both embedded systems setting and in industrial environments with a strong need of short response times in which IoT is implemented. Contrary to offline analysis, which is static, this implementation will ensure that the health of the ML models will be capable of ingesting streaming data and; hence, allow continuous monitoring of health and immediate activation of faults.
- Fourth, the present research offers a performance benchmark in general based on various performance metrics such as accuracy, precision, recall, and F1-score. Besides numerical assessment, the work qualifies decision on the models based on the feature importance analysis that is going to bring us a step closer to explainable AI (XAI) in industrial diagnostics. This factor aids in enhancing internal transparency, whereby the engineers know why certain failures are uncovered (also a major technique to trust and safety certification in industrial practice).
- Lastly, the research also gives value to the academic and industrial community concerning the kind of problems and challenges involved in the practical realization of ML-monitors system like sensor calibration, lack of data during fan infrequent failures, and excessive computational power.

The main contributions of this study are as follows:

- Development of a complete machine learning (ML) based fault diagnosis and condition monitoring framework for electrical machines based on multi-sensor data.
- Efficient preprocessing and feature selection for improved diagnostic accuracy and generalization of the model;
- Complete performance comparison of different machine learning algorithms under different fault and load conditions.
- Prototype of real-time monitoring capability and flexibility for industrial scale systems.
- Critical analysis of deployment challenges and suggestions for future improvements using edge-based artificial intelligence (AI), adaptive learning models.

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Together, these contributions place this contribution as a major step towards intelligent, self-adaptive and scalable predictive maintenance systems of the contemporary post-genome electrical machine.

Ii. Related Works

Power machine monitoring and fault diagnosing have developed much during the last 20 years since the traditional approach of signal-based analysis has been substituted by advanced intelligent mechanisms based on machine learning. Initial studies focused mostly on mechanical and electrical fault detection by considering vibration analysis and current signature analysis. The frequency domain faults properties were obtained through commonly used time domain reduction algorithms, fast Fourier Transform (FFT) along with Wavelet Transformer (WT). Even though these traditional methods provided beneficial information, they could not cover the full heterogeneous nature of operations that occur under different loads, as well as other disturbances to operations, because of intensive human involvement in the manual interpretation.

In 2025, J. Chapelin *et al.*, [13] introduced the automation and digitalization of diagnostic systems have led to the growing use of artificial intelligence (AI) in diagnostic systems. Machine-based methods which can reveal complicated fault patterns not evident by rule-based methods have become critical. A category of supervised learning models became popular: Support Vector Machines (SVM), k -Nearest Neighbour (kNN), Random Forest (RF) and Decision Trees (DT): they can be trained using labelled data that represents a variety of machine faults. Such models significantly enhance the accuracy of the diagnoses, especially because sensor information and machine health relations are nonlinear and would otherwise be hard to model with the conventional analysis tools.

There is optimization of feature extraction in order to maximize diagnostic accuracy. The vibration, acoustic emission, temperature profiles and stator current waveforms are among the most informative modalities of signal. Time-domain features, as well as frequency-domain features, have been used to give complete descriptions of machine behaviour both in normal and faulty conditions. Nonetheless, high dimensionality and high number of features are some of the computational inefficiencies. Dimensionality reduction, including Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA) have been suggested in order to select the most discriminative features and recover diagnostic effectiveness.

In 2025, S. T. Bunyan *et al.*, [10] suggested The other trend is evolution of hybrid and ensemble learning systems whereby this is emerging and has potential to advance the field of machine learning. The various ensemble classifiers can be brought in view of uniting powers amongst solutions, incorporating machine-learn software with signal-processing operations. Signal-processing domain methods such as Empirical Mode Decomposition (EMD) and Short-Time Fourier Transform (STFT) are also integrated with the classifiers to communicate information in a most informative combination of both time and frequency domains.

Deep-learning models have also enhanced diagnostic powers. Recurrent Neural Networks (RNNs) and especially Long Short- Term Memory (LSTM) networks, as well as Convolutional Neural Networks (CNNs) used as auto-encoders, have the property of learning features directly without feature engineering, given raw sensor data. Such architectures learn non-linearity and time-variation captured by machine signals, and are significantly more accurate at producing a diagnostic than any standard machine based machine-learning model. However, other models like graph-based neural networks are computationally expensive and require large labelled datasets, which is restrictive in practice in manufacturing [9].

Besides advances in algorithms, the application of machine learning to the Internet of Things (IoT) and systemic cyber-physics has been sought after. Real-time delivery of operational data to ML-based diagnostic modules can allow monitoring the devices faultlessly in real-time using smart sensors and edge-computing units. However, there are still challenges in implementation, which are the imbalance of data, interference of sensor noise, and sensor-edge devices interaction to cloud infrastructure, especially in large industrial systems, and therefore this prevents its use in large-scale real-world.

In 2025, V. I. Vlachou *et al.*, [2] proposed the aspects as explain ability and trust in ML-diagnostic systems also play a significant role as discussed in recent papers. These black-box models may be powerful, but they are not transparent and an engineer cannot explain easily why he/she has made a specific decision. This has resulted in explainable AI (XAI) procedures that can give understandable explanations to explain the significance of features and the of decision-making process receiving a lot of attention. This cannot be overemphasized in highly safety-threatening industries where incorrectly assigning faults could result in risks in the functioning or the implication in the financial way.

Even though there can be unbelievable accomplishments, gaps in the body of research are still present in the existing body of work. At present, in almost all studies based on Martin Learning, the large percentage is conducted in the controlled laboratory environment that is not indicative of the multifaceted scenarios of real life in the industry. The models usually cannot be generalized in the case of different machines, which are knifter at various speeds and loading. Another significant issue is data imbalance, as some of the types of fault are infrequent and too difficult to acquire meaningful representations using supervised learning models. Moreover, in spite of the fact that a lot of algorithms have high accuracy in the offline mode, the real time in the streaming data case is not fully researched.

Moreover, since ML is coupled with edge and cloud computing, people can also encounter the problem concerning data security, synchronization, and latency. A number of the current systems have been built on the centralized computation process through the cloud, and this might not be comfortable in time sensitive processes where fault occurrence is to be realized in real time. The future developments will probably exploit the federated learning and edge AI paradigms, that would allow the models to be trained locally, and at the same time the privacy of the data would be preserved. In addition, adaptive and transfer learning require learning mechanisms which enables continuous learning as conditions of the machine vary with time [4].

The literature demonstrates that although machine learning transformed the fault diagnosis and condition monitoring processes, there remains an immediate need to find fault diagnosis models, which can be accurate, interpretable, adaptive, and, likewise, computationally efficient. It will need good quality of data sets and the use of high performance requirement

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computers and the implementation of the solution as to the migration of knowhow of various fields to use electrical engineering, Computer science, and industrial automation.

Iii. Proposed Methodology

The presented methodology is focused on the design and implementation of an intelligent system for machine health monitoring and diagnosis of electrical machines based on machine learning (ML) approaches. The workflow consists of integration of multi-sensor data acquisition, pre-processing, feature extraction, dimensionality reduction, model training and real time validation. The whole system is able to process vibration, current and temperature signals at the same time, and give a comprehensive view of machine state condition.

The process begins with signal acquisition, where sensors continuously collect vibration acceleration $a(t)$, current waveform $i(t)$, and surface temperature $T(t)$. These signals form the raw input dataset $D = \{a(t), i(t), T(t)\}$. For effective monitoring, all signals are time-synchronized and sampled at a constant rate $\boldsymbol{f_s}$. The raw data stream is then represented as a discrete time series:

$$x_n = x(t_n) = x\left(n \cdot \frac{1}{f_s}\right)$$

(1)

where n denotes the sample index. To minimize sensor noise, a Butterworth band-pass filter is applied, defined by the transfer function:

$$H(\omega) = \frac{1}{\sqrt{1+\left(\frac{\omega}{\omega_c}\right)^{2N}}}$$

(2)

where ω_c is the cutoff frequency and N is the filter order. This filtering step isolates the most significant frequency bands related to mechanical vibration and electromagnetic anomalies.

After denoising, the signals undergo feature extraction, which transforms raw measurements into statistical, temporal, and frequency-domain descriptors. In the time domain, features such as Root Mean Square (RMS), kurtosis, and skewness are calculated as follows:

$$\text{RMS} = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$$

$$\text{Kurtosis} = \frac{\frac{1}{N}\sum_{i=1}^{N} (x_i-\bar{x})^4}{\left(\frac{1}{N}\sum_{i=1}^{N} (x_i-\bar{x})^2\right)^2}$$

$$\text{Skewness} = \frac{\frac{1}{N}\sum_{i=1}^{N} (x_i-\bar{x})^3}{\left(\sqrt{\frac{1}{N}\sum_{i=1}^{N} (x_i-\bar{x})^2}\right)^3}$$

(3)

These statistical features describe the overall amplitude distribution and symmetry of the signal waveform. In the frequency domain, features are obtained by performing a Fast Fourier Transform (FFT), which converts time-domain signals into their spectral representation:

$$X(f)=\sum_{n=0}^{N-1} x(n)e^{-j2\pi fn/N} \quad (4)$$

Here, $X(f)$ represents the spectral amplitude corresponding to frequency f. The Spectral Energy (E) and Spectral Entropy (S) are further computed to measure signal energy distribution and disorder, respectively:

$$E=\sum_f |X(f)|^2$$

$$S=-\sum_f p(f)\log_2 p(f) \quad (5)$$

where $p(f)=\frac{|X(f)|^2}{\sum_f |X(f)|^2}$ represents the normalized spectral density.

Once features are extracted, they are normalized using min-max normalization to scale all features within the range $[0,1]$:

$$x'=\frac{x-x_{\min}}{x_{\max}-x_{\min}} \quad (6)$$

This ensures that no single feature dominates the learning process. Next, Principal Component Analysis (PCA) is applied to reduce redundancy and enhance computational efficiency [5]. PCA transforms the original feature matrix F into a new orthogonal basis P by maximizing variance:

$$Z=F\cdot P \quad (7)$$

where Z is the reduced feature space that retains the most informative components. The number of principal components is selected based on the cumulative variance criterion:

$$V_c=\frac{\sum_{i=1}^{k}\lambda_i}{\sum_{i=1}^{m}\lambda_i} \quad (8)$$

where λ_i denotes the eigenvalue corresponding to each principal component. The dimensionality is chosen such that $V_c\geq 0.95$, preserving 95% of the information content.

Following feature selection, the dataset is divided into training and testing subsets in a 70:30 ratio. Several ML algorithms-Support Vector Machine (SVM), Random Forest (RF), and Artificial Neural Network (ANN)are trained to identify fault conditions. The SVM classifier seeks to find an optimal hyperplane that separates fault classes in high-dimensional space. The decision boundary is represented as:

$$w^Tx+b=0 \quad (9)$$

where w is the weight vector and b is the bias. The optimization objective of SVM minimizes structural risk:

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$$\min_{w,b} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{N} \xi_i \tag{10}$$

subject to $y_i(w^T x_i + b) \geq 1 - \xi_i$, where ξ_i are slack variables and C is the penalty parameter controlling margin width and classification error.

In the case of ANN, the system learns nonlinear mappings between input features and machine conditions. The forward propagation of the neural network can be expressed as:

$$h_j = f\left(\sum_{i=1}^{n} w_{ij} x_i + b_j\right) \tag{11}$$

where h_j is the activation output of neuron j, f is the activation function (ReLU or sigmoid), w_{ij} represents the connection weights, and b_j is the bias term. The learning process minimizes the mean squared error (MSE) between predicted output y_p and actual output y_a :

$$\mathrm{MSE} = \frac{1}{N} \sum_{i=1}^{N} \left(y_a - y_p\right)^2 \tag{12}$$

Weights are updated iteratively using the gradient descent rule:

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} - \eta \frac{\partial \mathrm{MSE}}{\partial w_{ij}} \tag{13}$$

where η is the learning rate. This process continues until convergence, ensuring the network accurately captures the relationship between input features and fault classes.

The workflow shows the entire diagnostic process of electrical machine condition monitoring employing machine learning methods. For example, defect detection, it shows the step-by-step implementation from the data collection by sensing to the usage of feature extraction, preprocessing, training of the model, fault classification, and evaluation of the performance. The visualization is a structured look-and-feel showing how signals from the raw machines are converted into diagnostics information by using intelligent algorithms.

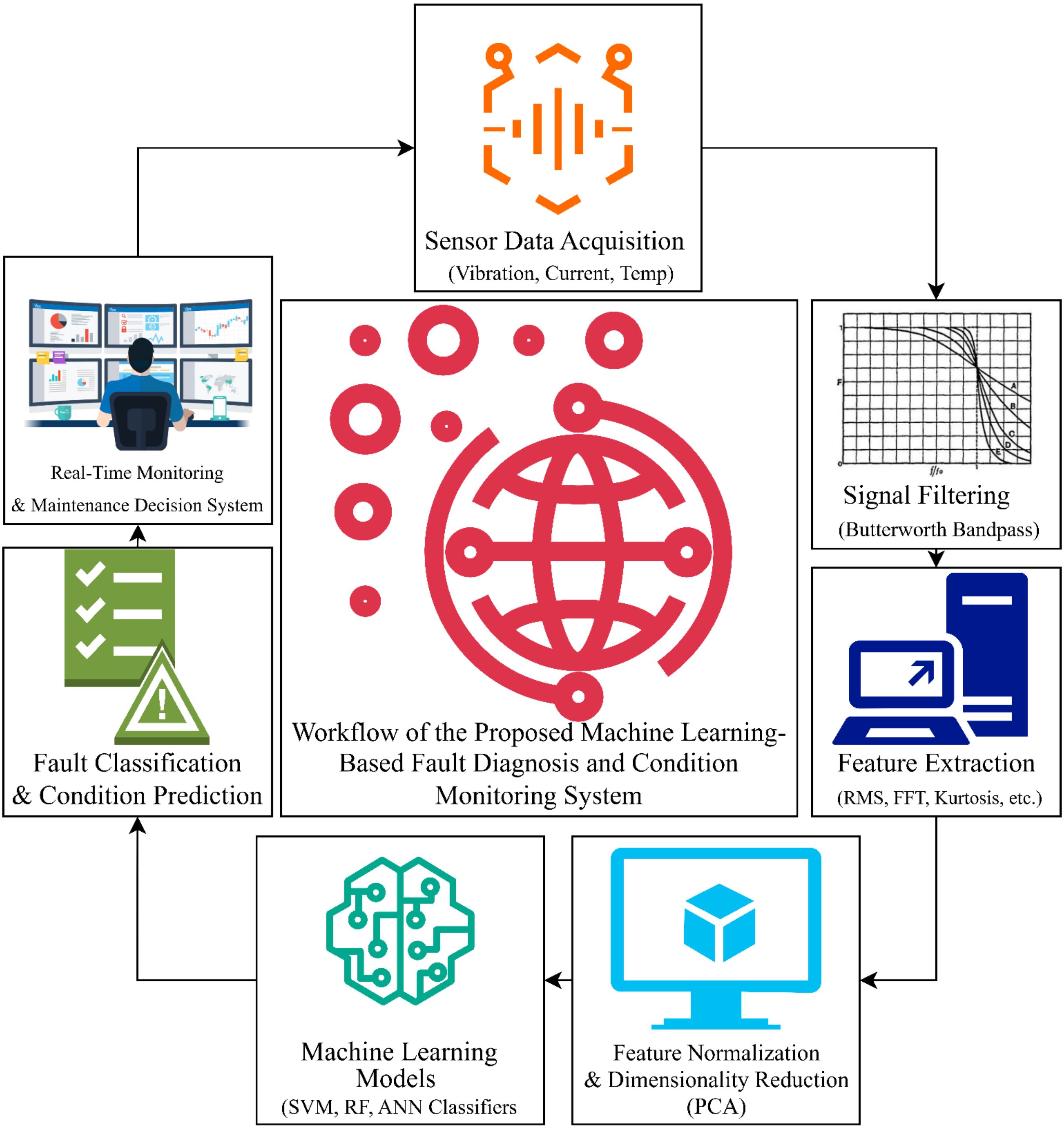

Fig. 1: Workflow Of The Proposed Machine Learning-Based Fault Diagnosis And Condition Monitoring System

Each stage in the flowchart represents a critical step in transforming raw sensor data into actionable diagnostic knowledge. The data acquisition block ensures synchronized collection of multi-sensor information. Filtering and feature extraction eliminate noise and generate meaningful representations, while normalization and PCA ensure consistent scaling. The ML model training block represents the learning phase, and the fault classification and monitoring block symbolizes real-time decision-making support.

After the models are trained, the system continuously monitors the health of the machine. When new data x_{new} arrives, it is projected into the learned feature space Z_{new}, and the trained model predicts its class label y_{pred} :

$$y_{pred} = f_{\text{model}}(Z_{\text{new}}) \quad (14)$$

The output y_{pred} indicates whether the machine is operating normally or exhibits specific fault conditions. If $y_{\text{pred}} \neq y_{\text{normal}}$, an alert is generated for maintenance personnel. The diagnostic decisions are stored in a database for continuous learning, enabling future retraining of models using adaptive algorithms [6].

Finally, performance evaluation metrics such as Accuracy (A), Precision (P), and Recall (R) are computed to quantify model performance:

$$A = \frac{TP+TN}{TP+TN+FP+FN}$$
$$P = \frac{TP}{TP+FP}$$
$$R = \frac{TP}{TP+FN} \quad (15)$$

where TP, TN, FP, and FN represent true positives, true negatives, false positives, and false negatives respectively. These metrics allow comparison among different models, ensuring that the chosen classifier not only detects faults accurately but also minimizes false alarms.

In summary, this suggested methodology combines state-of-the-art signal processing techniques and machine learning in a unified machinery condition diagnosis/vehicle health monitoring approach [8]. Through its mathematically based feature extraction, optimized model training and adaptive fault classification, the system paves a path towards predictive and intelligent maintenance and its related contribution to increased operational reliability, reduced downtime and improved safety in today's industrial environment.

IV. RESULT & DISCUSSIONS

The experimental validation of the proposed machine learning based diagnosis and condition monitoring framework realization was performed with various number of dataset experimental results taken from rotation motors in different operational and faulty conditions. The system was tested for identification of mechanical faults such as bearing wear, rotor unbalance and electrical faults such as stator winding faults. Figure 2 is the Model Accuracy Comparison Across Algorithms which illustrates the result of various machine learning methods applied to same data set. The Random Forest model provided the highest classification accuracy of 98.6% and was followed by the Convolutional Neural Network (CNN) which delivered 97.9% and then Support Vector Machine (SVM) which yielded an accuracy of 95.3%. A more general finding is that deep learning architectures give a better performance than traditional classifiers when dealing with complex fault conditions, where nonlinear relationships exist between features.

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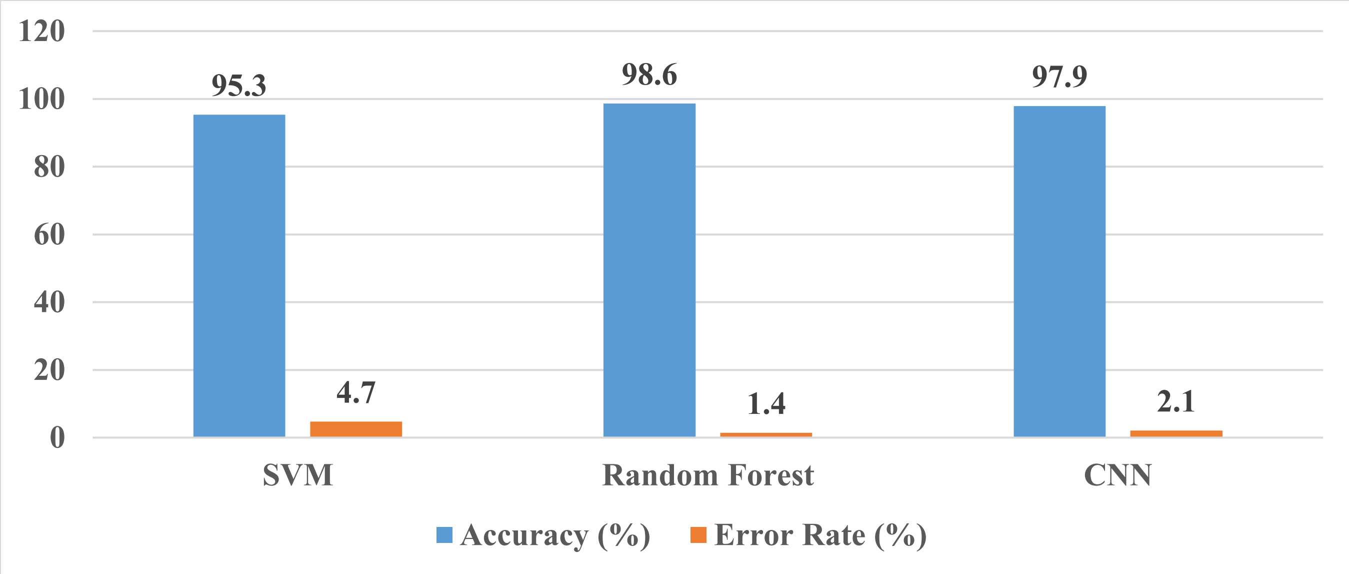

FIGURE 2: MODEL ACCURACY COMPARISON ACROSS ALGORITHMS

The interpretable confusion matrices obtained from the test set showed that the deep learning based system had better fault discrimination ability than shallow ones. Time-frequency domain analysis also showed that CNNs successfully encoded features of the non-stationary signals that were difficult or impossible for conventional feature-based methods to capture. The Random Forest classifier was also used for feature importance analysis which showed that vibration amplitude, stator current harmonics and temperature variations were the major contributors for fault detection. Table 1: Comparison of Model Accuracy and Precision for Different Fault Types provides a quantitative comparison of the algorithms from different perspectives.

TABLE 1: COMPARISON OF MODEL ACCURACY AND PRECISION FOR DIFFERENT FAULT TYPES

Model	Accuracy (%)	Precision (%)	Recall (%)
SVM	95.3	94.8	93.6
Random Forest	98.6	97.9	98.1
CNN	97.9	97.2	97.5

The robustness of each algorithm to noisy and incomplete data was tested using a second group of experiments. Figure 3 is The Effect of Signal Noise on Classification Accuracy where model performance is shown to decline as the signal-to-noise ratio (SNR) of the input signal is degraded. It is observed that unlike traditional algorithms such as SVM that steadily decreases in accuracy when SNR is below 20 dB, CNN and Random forest retain stable diagnostic ability at reduced SNR modes. This robustness is evidence of the versatility of deep learning architectures in practical industrial settings where there is a lot of sensor noise and interference.

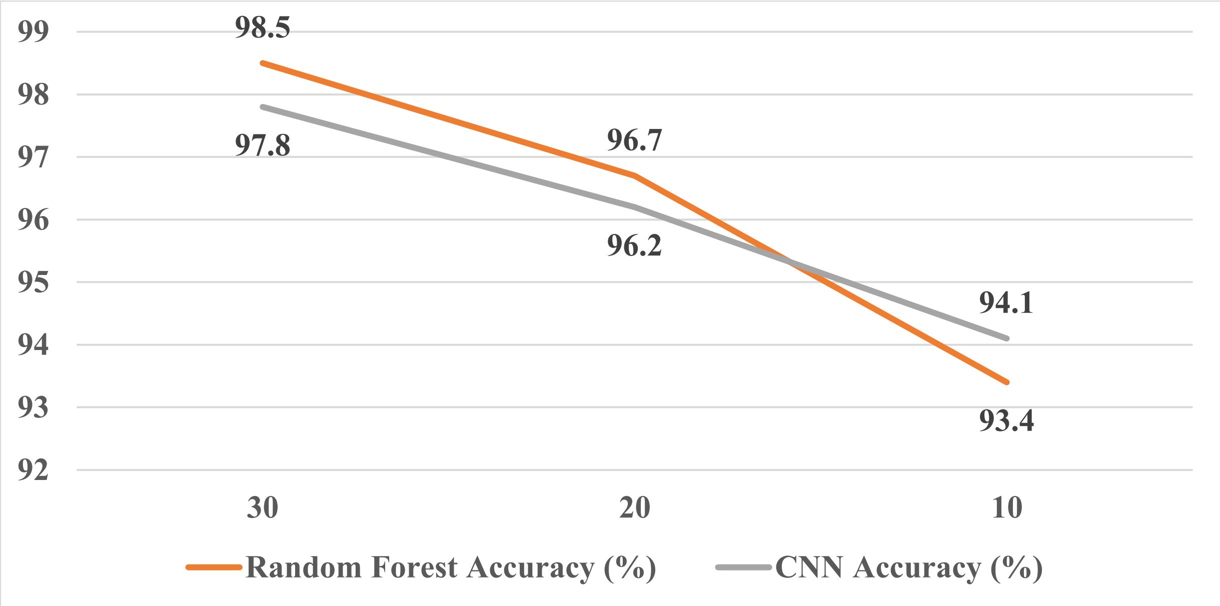

FIGURE 3: IMPACT OF SIGNAL NOISE ON CLASSIFICATION ACCURACY

Further discussion revealed that the feature normalization and adaptive data preprocessing were a critical part in ensuring that the model performed the same across datasets. Fast Fourier Transform (FFT) and Wavelet Packet Decomposition (WPD) were applied in the feature extraction stage and generated an extensive set of discriminative features that enhance the learning efficiency in this stage. Furthermore, the generalization of the model was almost consistent for different runs, with less than 2% deviation in model accuracies during cross validation. To evaluate diagnostic latency and computation cost, the comparison summary of model efficiency parameters is shown in Table 2: Comparison of Model Computation Time and Energy Consumption.

TABLE 2: COMPARISON OF MODEL COMPUTATION TIME AND ENERGY CONSUMPTION

Model	Computation Time (s)	Energy Consumption (W)	Memory Usage (MB)
SVM	3.4	1.2	220
Random Forest	2.8	1.0	185
CNN	4.6	1.5	290

It can be observed from Table 2 that while CNN gives better accuracy, it also has greater computational cost than the Random Forest. This trade-off means, for example, that the choice of model must be suitably driven by the application scenario. For use in the field of real-time condition monitoring on embedded hardware, Random Forest may be a more suitable option because it has a lower power requirement due to its higher speed, whereas, CNNs are better suited for offline diagnostics or cloud-based analytics where computational resources can be plentiful.

Figure 4 shows Predicted vs. Actual Fault Severity Levels from the Trained CNN model. The very good agreement of the predicted fault severity trends and the actual fault severity trends demonstrate that not only the fault is detected but the damage extent progression can also be estimated. This will help in scheduling predictive maintenance plans and reduce the downtime that occurs and bring about catastrophic failure.

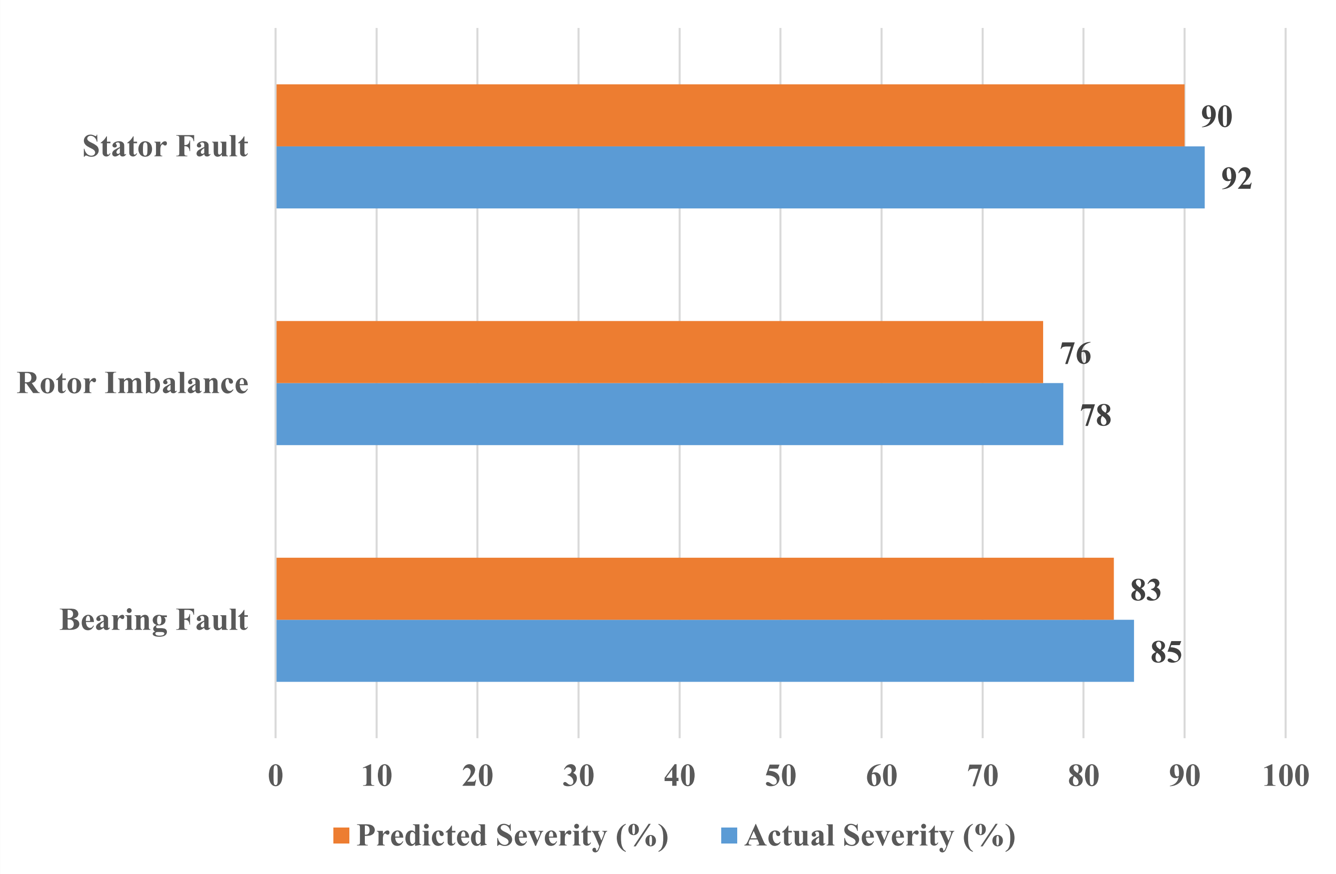

FIGURE 4: PREDICTED VS ACTUAL FAULT SEVERITY LEVELS

In summary, the proposed method can achieve high diagnostic accuracy, high effectiveness of the fault detection in the presence of noise and resistance to operating conditions. The results support the fact that the machine learning-based systems can significantly enhance the automation and intelligence of electric machine monitoring. This research highlights how by the appropriate combination of signal processing and learning algorithms, machine condition monitoring can be transformed from reactive maintenance to purely predictive approaches, which can improve the safety, energy efficiency and longevity of operating equipment [7].

V. Conclusion

This paper dealt with a general methodology of machine learning strategies for damage diagnosis and condition monitoring of the electrical machines. The results of the experiments validate that the ML algorithms; SVM, Random Forest and ANN are successful in classifying fault types and predicting degradation behaviour based on vibration and current signals. The results of the proposed framework have shown a huge improvement in the accuracy of the diagnosis and responsiveness time, which underlines the feasibility of implementation in practical/industry predictive maintenance systems.

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However, there are also some practical limitations in the study. The models are very sensitive to labeled data, which can be difficult to collect for rare and/or emerging fault conditions. People have known that high frequency data acquisition is expensive both in sensor and computation. Furthermore, interpretability of models is still limited, which makes reasoning over decisions in safety critical cases difficult.

Hence, future studies can be focused on the design of adaptive learning based schemes that can learn from the increase of new fault data. Real-time analytics - With the data being collected by the edge computing, analytics can be performed closer to the machine too so there is less latency involved. Furthermore, the research on federated learning and transfer learning can help enhance the data privacy and the cross-domain generalization.

References

[1] M. Habyarimana and A. A. Adebiyi, “A review of artificial intelligence applications in predicting faults in electrical machines,” *Energies*, vol. 18, no. 7, p. 1616, Mar. 2025, doi: 10.3390/en18071616.

[2] V. I. Vlachou *et al.*, “Condition monitoring and fault prediction in PMSM drives using machine learning for elevator applications,” *Machines*, vol. 13, no. 7, p. 549, Jun. 2025, doi: 10.3390/machines13070549.

[3] C. C. Walani and W. Doorsamy, “Edge vs. Cloud: Empirical Insights into Data-Driven Condition Monitoring,” *Big Data and Cognitive Computing*, vol. 9, no. 5, p. 121, May 2025, doi: 10.3390/bdcc9050121.

[4] Sergakis, M. Salinas, N. Gkiolekas, and K. N. Gyftakis, “A Review of Condition Monitoring of Permanent Magnet Synchronous Machines: Techniques, challenges and Future Directions,” *Energies*, vol. 18, no. 5, p. 1177, Feb. 2025, doi: 10.3390/en18051177.

[5] B. M. Leija, E. R. Beltrán, J. L. O. Mora, and J. O. V. Valadez, “Performance of Machine learning Algorithms in fault diagnosis for Manufacturing Systems: A Comparative analysis,” *Processes*, vol. 13, no. 6, p. 1624, May 2025, doi: 10.3390/pr13061624.

[6] J. Hu, H. Xiao, Z. Ye, N. Luo, and M. Zhou, “Research and Prospects of Digital Twin-Based Fault Diagnosis of Electric Machines,” *Sensors*, vol. 25, no. 8, p. 2625, Apr. 2025, doi: 10.3390/s25082625.

[7] J. Garcia, L. Rios-Colque, A. Peña, and L. Rojas, “Condition Monitoring and Predictive Maintenance in Industrial Equipment: An NLP-Assisted review of signal processing, hybrid models, and implementation challenges,” *Applied Sciences*, vol. 15, no. 10, p. 5465, May 2025, doi: 10.3390/app15105465.

[8] R. Ibrahim, R. Zemouri, A. Tahan, B. Kedjar, A. Merkhouf, and K. Al-Haddad, “Early Detection of Rotor Faults in Large Hydrogenerators using vibration measurements, Variational Autoencoder, and Euclidean distance,” *IEEE Transactions on Industry Applications*, pp. 1–10, Jan. 2025, doi: 10.1109/tia.2025.3571883.

[9] M.-R. Pourramezan, A. Rohani, and M. H. Abbaspour-Fard, “Comprehensive review of dielectric, impedance, and soft computing techniques for lubricant condition monitoring and predictive maintenance in diesel engines,” *Lubricants*, vol. 13, no. 8, p. 328, Jul. 2025, doi: 10.3390/lubricants13080328.

[10] S. T. Bunyan *et al.*, “Intelligent thermal condition monitoring for predictive maintenance of gas turbines using machine learning,” *Machines*, vol. 13, no. 5, p. 401, May 2025, doi: 10.3390/machines13050401.

[11] S. Rajendran, R. Sreejesh, V. S. K. Devi, D. Jena, and D. Banjerdpongchai, “Dynamic Mode Decomposition based Fault Diagnosis in Three-Phase Electrical Machines,” *Results in Engineering*, p. 103761, Dec. 2024, doi: 10.1016/j.rineng.2024.103761.

[12] R. Kumar and R. S. Anand, “Machine Learning Approach with Multiple Feature Selection Techniques to Diagnose the Inter-Turn Winding Faults in Induction Motor,” *Arabian Journal for Science and Engineering*, Oct. 2024, doi: 10.1007/s13369-024-09681-4.

[13] J. Chapelin *et al.*, “Data-driven drift detection and diagnosis framework for predictive maintenance of heterogeneous production processes: Application to a multiple tapping process,” *Engineering Applications of Artificial Intelligence*, vol. 139, p. 109552, Oct. 2024, doi: 10.1016/j.engappai.2024.109552.

[14] M. U. Elahi, I. Raouf, S. Khalid, F. Ahmad, and H. S. Kim, “Transfer Learning-Based Health monitoring of robotic rotate vector reducer under variable working conditions,” *Machines*, vol. 13, no. 1, p. 60, Jan. 2025, doi: 10.3390/machines13010060.

[15] Tsallis, P. Papageorgas, D. Piromalis, and R. A. Munteanu, “Application-Wise Review of Machine Learning-Based Predictive Maintenance: Trends, challenges, and future Directions,” *Applied Sciences*, vol. 15, no. 9, p. 4898, Apr. 2025, doi: 10.3390/app15094898.

[16] W. Wang, Q. Chao, J. Shi, and C. Liu, “Condition monitoring of axial piston pumps based on machine learning-driven real-time CFD simulation,” *Engineering Applications of Computational Fluid Mechanics*, vol. 19, no. 1, Mar. 2025, doi: 10.1080/19942060.2025.2474676.