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A Comprehensive Review of Machine Learning Algorithms for Fault Diagnosis and Prediction in Rotating Machinery

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Abstract

Machine learning (ML) algorithms for detecting defects and predictive maintenance of industrial equipment have emerged as a set of critical methods for improving operational efficiency, reducing unexpected downtime, and extending machinery life. This study presents a comprehensive examination of various machine learning models, signal processing approaches, and reduced dimensionality methods for monitoring system health and detecting possible flaws based on research published in the last five years. Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Genetic Algorithms (GA), Multi-Layer Perceptron (MLP), and Fully Connected Neural Networks (FCNN) are utilized for classifying fault patterns coming from sensor data. In contrast, signal processing techniques such as Mel-Frequency Cepstral Coefficients (MFCC) and Short-Time Fourier Transform (STFT) are used to collect significant features from vibration and acoustic signals. Dimensionality reduction approaches such as Principal Component Analysis (PCA), t-distributed Stochastic Neighbour Embedding (t-SNE), ISOMAP, Independent Component Analysis (ICA), and Autoencoders (AE) are used to simplify complex data structures and show crucial defect signals. Random Forest, K-Nearest Neighbours (KNN), and CatBoost are some of the algorithmic ensembles learning methods studied for prediction accuracy and robustness. Furthermore, advanced deep learning models, such as 1D Deep Convolutional Neural Networks (1D-DCNN) and ResNet-3N, are utilized to capture temporal and spatial patterns in time-series data, leading to a more complete comprehension of fault dynamics. The research shows the effectiveness of these various approaches in boosting fault detection systems and improving maintenance techniques, paving the way for intelligent technologies in modern manufacturing.

Keywords: Machine Learning; Vibration Analysis; Rotating Machines; Fault Detection.

1.Introduction

One of the most crucial aspects of running a plant or manufacturing facility is the maintenance of electric power plants, as the adopted maintenance methodology will significantly impact the plant's downtime and profitability [1].

Reducing planned and unplanned downtime, increasing production equipment availability, and enhancing safety are the primary objectives of maintenance. Corrective, preventive, and proactive maintenance (CBM) are the three main categories of maintenance ideologies [2].

When equipment fails or there are unplanned outages, corrective maintenance is performed, and preventive maintenance is based on scheduling over time utilizing simple inspection techniques such as vibration and temperature [3],[4].

Predictive maintenance or condition monitoring techniques (CBM) are regarded as one of the most important types of maintenance. It depends on the state of the equipment and precise diagnosis by a skilled team with expertise in vibration analysis, thermal imaging, oil analysis, and ultrasonic devices [5],[6].

Vibration analysis and oil analysis are two essential elements of CBM, each of which offers significant perspectives into the equipment's operational condition. Particularly for rotating mechanical and electrical systems, vibration monitoring is a crucial maintenance technique for observing equipment performance and scheduling timely maintenance operations as a crucial part of maintenance programs [7],[8].

Vibration monitoring can detect early fault alerts based on the machine’s actual state. The study of mechanical vibration in rotating machines is known as vibration analysis, and it is a low-cost way to keep an eye on the efficiency and condition of mechanical industrial equipment while it is in use. When fitted with sensors, real-time diagnosis and treatment can be achieved through gathering data, analyzing it, and interpreting it. The diverse and complex machinery used in factories and power plants, such as engines, pumps, gas and steam turbines, and other rotating mechanical and electrical systems, poses significant challenges. These machines are essential to the production process, making their smooth operation vital for overall efficiency [9].

To avoid unforeseen damage, lower maintenance costs, and guarantee the safety of the finished products, anomalies or deviations in operation must be promptly detected. In this case, vibration analysis is helpful. Vibration analysis measures the vibration behaviours of machinery to diagnose misalignment, imbalances, bearing faults and other mechanical issues [10],[11],[12].

Regular oil analysis is an effective way to detect abnormal wear or contamination by determining the level of normal wear as a basis for comparison. Comprehensive oil sample testing is a valuable tool for preventive maintenance, as it can detect potential problems before major repairs are needed and can help reduce the frequency of oil changes. The data generated by oil analysis is divided into three categories: Inspection of machinery lubricating fluids for wear particles, deterioration, and contaminants. Solubility, viscosity, heat capacity, wettability, damping ability, and resistance to wear and friction are all characteristics of lubricants and liquid lubricants that have helped them broaden their range of applications over time. Engineers have added solid particles to these materials to take advantage of their synergistic effect in reducing friction and wear. Tribologists have also developed superior lubricants that offer low volatility, high thermal stability, and a wide fluid range [13].

As a result, the list of lubricants as well as their properties has become so numerous nowadays that it is challenging even for experts to choose the best lubricant or predict the optimum condition of a selected material without going through multiple experiments. Additionally, oil analysis is crucial for maintaining equipment reliability and extending its service life [14].

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Although traditional techniques allow data analysts to identify failures caused by friction and take necessary actions, early prediction can reduce failure time and increase maintenance efficiency. For this reason, tribologists have made their mark in the field of computational analysis to improve predictions [15]. Vibration and oil analysis combine to provide a comprehensive CBM strategy that reduces maintenance costs, improves machine reliability, and reduces unscheduled downtime. By implementing these measures, industries may ensure that their equipment performs as well as possible [16],[17],[18].

In this research investigation, machine learning techniques were utilized to detect industrial machinery failures and highlight the significance of performing predictive maintenance regularly. This study underlines the value of diagnosis in discovering and treating flaws. The goal of this research is to determine the most acceptable algorithms for real-time applications by analyzing their benefits, drawbacks, and accuracy. Furthermore, the findings contribute to the development of more robust and effective diagnostic tools, thereby improving operational efficiency in manufacturing environments. The study underlines the usefulness of machine learning algorithms for better monitoring and choice-making processes.

Figure 1. Vibration measurement of the motor

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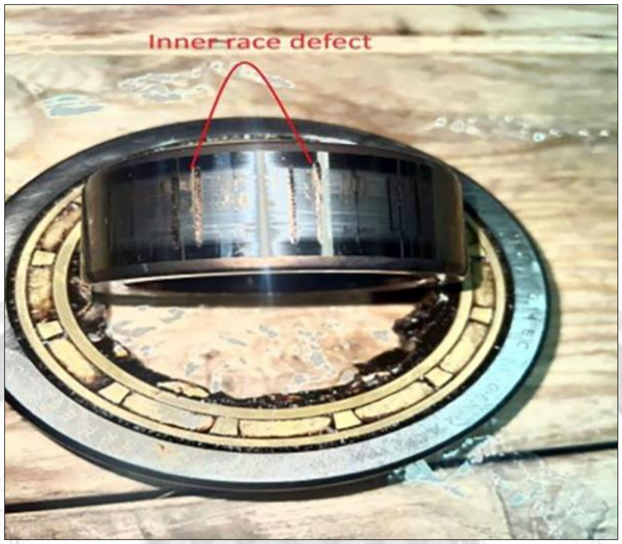

Figure 2. Identification of bearing defects of the motor

2. Literature Review

Several investigations focused on detecting faults in industrial machinery by applying machine learning methods. Roberto Alexandre Dias et al., 2020 [19] created a platform that uses the latest developments in machine learning and sensor technology to provide predictive maintenance, spotting issues before major breakdowns happen. A supervisory system that records high-frequency vibration data evaluates how a machine operates and determines whether its behaviour is normal or abnormal, producing alarms. Said Haggag et al.,2022 [20] modelled an ETRR-2 research reactor core coolant pump vibration monitoring utilizing an artificial neural network (ANN). The ANN model uses the vibration transducer's input and output signals as source data. The ANN receives input from the frequency domain and amplitudes independently of the vibration data. ANNs are utilized to identify anti-friction, loose bearings, misalignment, and the degree of imbalance.

Seon Woo Lee et al., 2021[21] proposed a predictive maintenance model that can proactively prevent failures in hypergravity accelerators. The proposed method involves converting vibration signals into spectrograms and conducting classification training using a deep learning model. The bearing casing (a rotor) was fitted with a four-channel accelerometer, and time-amplitude data were sampled from the measured values. Following the conversion of the data into two-dimensional spectrograms, a deep learning model was used for four equipment conditions: imbalance, misalignment, shaft friction, and normal. Results showed that the proposed method has an accuracy of 99.5%, a 23% increase compared to current learning-based models.

Neural networks, KNNs, and CatBoost were investigated by Salman Yusuf Ibrahim et al, 2023 [22] Over 90% of maintenance and repair needs were accurately forecasted by machine learning techniques. The service estimation date was also determined by algorithms, which enhanced the scheduling of maintenance and repairs. It enhanced reliability, decreased downtime and enhanced maintenance, and repaired procedures. In Xiaopeng Liu et al.,2023 [23] a fault detection model based on CNN was suggested to diagnose the motor failure, aiming to address the issue that damaged bar fault and rotor eccentricity are difficult to detect in induction motors.

The suggested CNN model offers a knowledgeable, effective, and perceptive answer for identifying induction motor problems. Dilated convolution speeds up the training process and offers better convergence and accuracy than other CNN algorithms. The signals under typical operating conditions and two fault states and conditions are gathered. Next, the database of faults with a single period as the sample has been determined, and the model learns features from data on motor vibration and acceleration on its own and simultaneously recognizes different kinds of faults.

Roberto M. Souza et al.,2020 [24] suggested the classification of automatically rotating equipment defects and the recommendation of when maintenance should be performed using the predictive maintenance model using a Convolutional Neural Network (PdM-CNN). In their study, they used data from a sensor mounted on the drive-end bearing of the motor. To determine whether it is feasible to construct a model that can categorize such problems in rotating machinery using a single set of vibration sensors, this work was produced under controlled atmospheric conditions with varying rotational speeds, load levels, and severity. The PdM-CNN model's accuracy was 99.58% and 97.3%, respectively. Vijyalakshmi K., 2024 employed four methods to check machine conditions, a modern artificial intelligence (AI) method for detecting faults in a wide range of machinery. Deep learning techniques were evaluated utilizing Spectra Quest Machinery Fault Simulator (SQMFS) vibration datasets. Recurrent neural networks (RNN), multilayer perception (MLP), and coevolutionary neural networks (CNN) with long short-term memory (LSTM) were used for defect detection. Vibration signals were collected using an accelerometer, LabVIEW software, and an NI-DAQ (National Instruments-Data Acquisition) system. The signals were preprocessed using a sampling technique, shuffling, normalization, reshaping, and data augmentation. The results show that CNN's MLP accuracy in fault prediction is 0.9. RNN and LSTM obtained 0.57 and 0.45, respectively, while CNN obtained 0.95. The study found that CNN outperformed various other deep-learning systems, such as MLP, RNN, and LSTM, in predicting rotating equipment flaws.

Iulian Lupea and Mihaiela Lupea, 2023 [26] developed a system for examining and identifying mounting flaws on a rotating test rig. The test rig is made up of a thin shaft with a central disc that is symmetrically supported by ball bearings that oscillate. Through a timing belt, the shaft is pushed at a steady speed with very few deviations. Defects are imposed on the timing belt mounting position or motor reducer position, the eccentricity of the disc, and the translation of the central disc along the shaft. Fault detection uses time and frequency domain parameters that are taken from the vibration signal as predictors. The classes in this task represented eight health states, one healthy and seven defective, which were described as a multi-class classification issue. By applying both supervised and unsupervised methods, data analysis provides valuable insights such as feature relevance, feature correlation, classification challenges, and data visualization, leading to a more balanced and informative dataset. Six feature sets and MATLAB classifiers were used in the studies. The best results have been achieved using SVM with 98.93% accuracy for the subset of the 18 most important features and 99.18% accuracy for all 41 features retrieved from axes of the X and Y sensors.

3. Methodologies of Machine Learning Algorithms

A method has been developed to identify machinery defects using machine learning algorithms. The process involves several key steps: [27],[28].

- Data Acquisition: Collect historical data from machinery, which includes sensor measurements, operational characteristics, and maintenance records. This data can be gathered using various sensors, such as temperature, vibration, and pressure sensors.
- Data Preprocessing: Cleanse and prepare the data by removing noise and irrelevant information. This step may include normalization, addressing missing values, and converting categorical data into numerical formats.
- Feature Extraction: Identify and extract key features that contribute to faulty conditions. Relevant features may include statistical metrics, time-domain attributes, frequency-domain characteristics (utilizing methods such as Fast Fourier Transform), and potentially domain-specific traits.
- Model Selection: Choose the appropriate machine learning methods for diagnostic problems. Commonly used approaches include:
  - Decision Trees for straightforward classification tasks.
  - Support Vector Machines (SVM) for differentiating fault and non-fault categories in complex data spaces.
  - Neural Networks (deep learning models) for handling more sophisticated, high-dimensional datasets.
  - Ensemble Learning methods (such as Random Forest and Gradient Boosting) which combine multiple models to enhance performance.
- Model Training: Divide the data into training and testing sets. Train the selected machine learning model using the training data, enabling it to learn patterns associated with normal and faulty operations.
- Model Evaluation: Assess the performance of the model using metrics such as accuracy, precision, recall, and F1 score based on the testing set. This evaluation phase helps determine how effectively the model can identify errors.
- Fault Diagnosis: Use the trained model to analyze real-time data from machines to predict and detect defects. The model should classify the operational condition of the machine based on the input features. Fault detection in machinery is essential for predicting potential failures, improving operational efficiency, and minimizing downtime. Machine learning algorithms have become increasingly popular in this field due to their ability to process large datasets, learn from historical data, and identify anomalies that indicate faults.

These models utilize a range of techniques, from conventional techniques for machine learning such as Support Vector Machines (SVM) and Random Forest to sophisticated deep learning models such as CNNs (Convolutional Neural Networks), Residual Networks (ResNets), and Deep Convolutional Neural Networks (DCNNs). The accuracy rates indicate that each model was finely tuned for specific types of data or tasks.

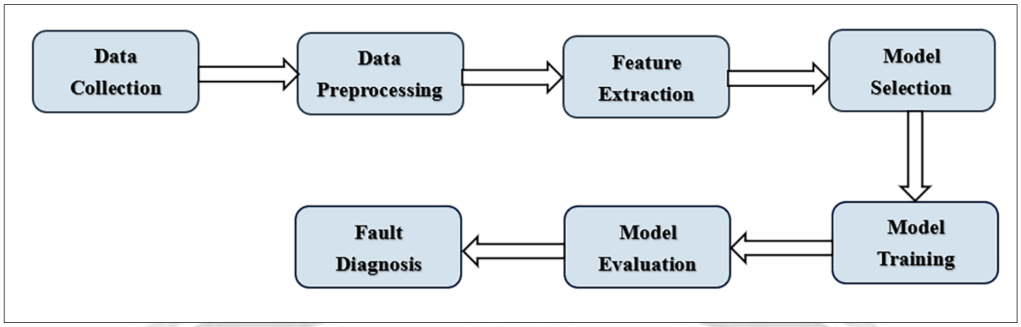

Figure 3. Scheme of a typical fault diagnosis process

4. Fault Diagnosis and Prediction in Rotating Machinery

The fault diagnostic method for rotating equipment begins with the collection of vibration data, followed by the reduction of signal noise and the extraction of damage-characteristic signals to determine the faulty state, as well as the problem severity [31],[32].

4.1. Signal Analysis

- Vibration analysis for condition tracking systems uses vibration sensors to capture the frequencies in a machine and find anomalies that could indicate an issue. Vibration analysis is fundamentally concerned with the oscillating motions of machines and their elements around a predetermined equilibrium point. These oscillations can be caused by a variety of troubles such as misalignments, unbalances, looseness, bent shafts, and bearing flaws.
- Monitoring the current and voltage powering the motors is critical to overcoming electrical difficulties caused by winding defects, rotor troubles, or electrical imbalance.
- High-frequency acoustic emissions can indicate mechanical faults like cracks or bearing wear.

4.2. Faults in Rotating Machinery

The most common mechanical breakdowns in rotating machinery are characterized as [33]:

- Misalignment happens if two or more components, including coupling components, bearings, shafts, and pulleys, are not aligned precisely and cause severe vibrations in the axial and radial directions.
- Unbalance is the most common cause of mechanical damage in rotating machinery caused by an irregular distribution of rotating masses.
- Bearing failures can happen for a variety of causes, including lubrication failure, wear and tear, and long-term use without maintenance.
- Gearbox failures occur due to misalignment, lubrication problems, and tooth wear.

- Cavitation is caused by pressure variations inside pumps collapsing and producing waves of shock that recur repeatedly, destroying the components. In numerous instances, the force of cavitation can be powerful sufficient to break down metal pump components such as the impeller and cause pump seal failure.

4.3. Techniques for Fault Detection

- Time-domain analysis: Look for spikes or variations in the signal as it moves through time.
- Frequency-domain analysis: Fourier transformations are utilized to transfer the time-domain data into the frequency domain, which allows the definition of characteristic fault frequencies (such as bearing fault frequencies).
- Wavelet Transform: An advanced signal processing approach that improves resolution in both time and frequency [34],[35].

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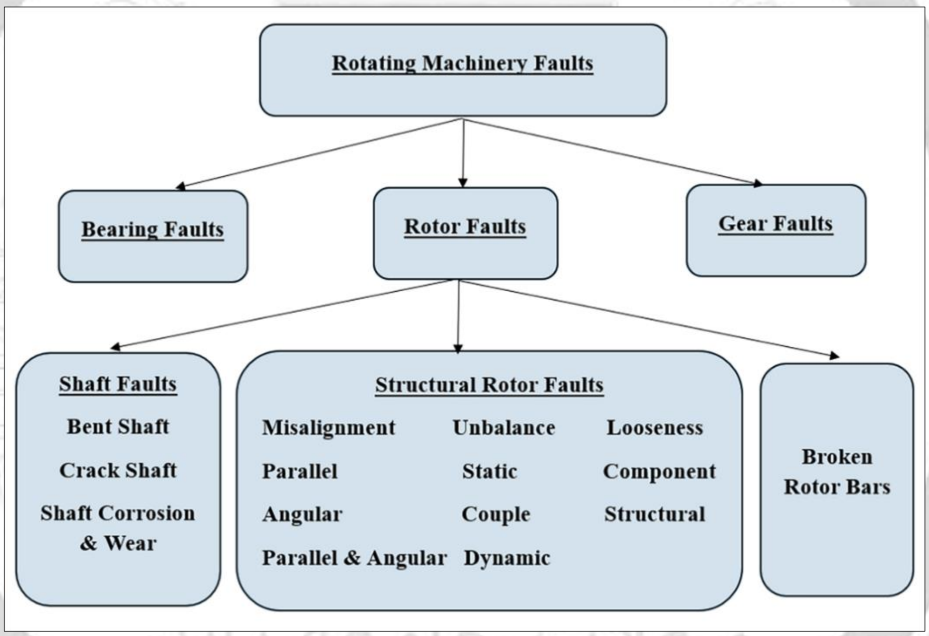

Figure 4. Categorization of rotating machinery faults

Table 1. Prognosis And Diagnosis of Faults of Components in a Rotating Machine Using Machine Learning Algorithms [36].

Component Fault	Machine Learning Algorithms
Bearing	CNN, GA
Bearing	CNN, MLP, SVM, KNN
Bearing, Rotor	CNN
Bearing, Rotor	CNN, SVM, KNN
Bearing	CNN, SVM
Rotor	CNN, SVM, KNN

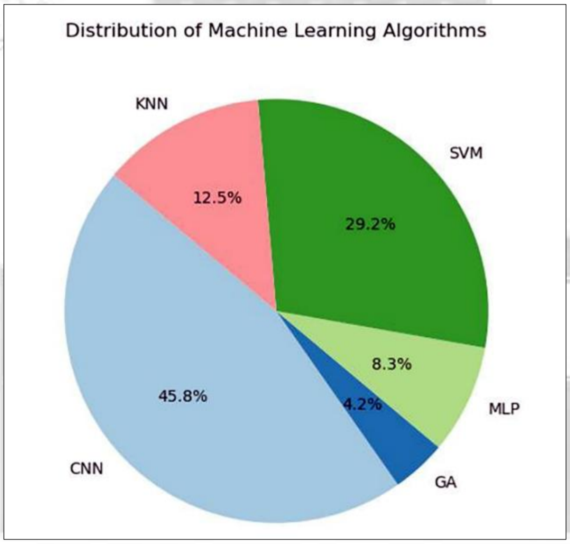

Figure 5. Flow chart of machine learning algorithms distribution

5. Advantages of Machine Learning for Fault Diagnosis in Machinery

The advantages of employing machine learning for fault diagnosis in equipment include faster and more accurate defect identification due to its ability to process big datasets. It provides predictive maintenance by identifying possible issues before they cause failure, hence decreasing downtime. The advantages of machine learning algorithms include their ability to adapt to new fault patterns and improve with constant data input. However, its disadvantages include the need for large volumes of labelled data for training, which can be difficult to obtain. Noisy or inadequate data might reduce model accuracy, resulting in incorrect diagnoses.

6. Mathematical Modeling of Machine Learning Techniques

6.1. MLP

The Multi-Layer Perceptron (MLP) is a supervised learning model designed for non-linear problems with its multi-layer architecture. It consists of an input layer, hidden layers, and an output layer, with neurons fully connected and weights adjusted to process data. Each neuron computes its output through an activation function, and the network is trained using feedforward and backpropagation to minimize errors. Hyperparameters like the number of layers, neurons, and activation function significantly affect training performance and

efficiency. Each hidden layer is composed of several artificial neurons, and the output of an artificial neuron is obtained through equation (1) [16].

$$y = f\left(\sum_{i=1}^{p}(w_i x_i + b)\right) \quad (1)$$

Where: f is the activation function (e.g., sigmoidal function, exponential linear unit, hyperbolic tangent function, or rectified linear unit), p is the number of inputs, w is the input vector, x is the input signal vector of the neuron, b represents the polarization value.

6.2.CNN

A Conventional Neural Network (CNN) is a type of deep neural network designed to process grid-like data, such as images. CNNs use convolutional layers to apply filters that detect local patterns (e.g., edges and textures), followed by activation layers like ReLU for non-linearity. Pooling layers reduce spatial dimensions, and fully connected layers perform classification based on extracted features. The learning process is driven by backpropagation to adjust parameters and minimize errors. CNNs excel in image recognition tasks due to their ability to capture hierarchical patterns in data, leading to breakthroughs in computer vision applications. A basic convolution operation in CNN is shown in equation (2) [29,30]:

$$S(i,j) = (I * K)(i,j) = \sum_{m-0}^{M-1}\sum_{n-1}^{N-1} I(i+m, j+n).K(m,n) \quad (2)$$

Where: S(i,j) is the output at position (i,j), I is the input matrix (image), K is the kernel (filter) matrix, and (m,n) are coordinates of the kernel applied to the input.

6.3. D-DCNN

1-Dimensional Deep Convolutional Neural Network (1D-CNN) is a neural network that processes one-dimensional data like time series, audio, or text. This network applies the convolution operations along a single dimension, as opposed to 2D-CNN, which operates on two-dimensional data (e.g., pictures), and 1D-CNN is suitable for tasks such as flaw detection in machinery.

1D-CNN output is calculated as follows [23]:

$$O_t = \sum_{k=0}^{k-1} w_k^l \, x_t + \left(k - \frac{k-1}{2}\right).d_l \quad (3)$$

Where: d_l is the expansion rate, w_k^l l is the convolution kernel parameter, k is the convolution kernel size.

6.4. SVM

The Support Vector Machine (SVM) is a model used for supervised learning for tasks such as classification and regression. They work by identifying the hyperplane that best divides data into various classes. SVM is very effective for fault detection in machinery since it identifies machine states (e.g., “normal” or “faulty”) using features collected from sensor data including vibration and temperature or auditory signals. The output is calculated as follows [16].

$$Y = f(x) = W_X^T + b = \sum_{i=1}^{N} W_I X_i + b \tag{4}$$

Where N represents the number of samples, W is an N-dimensional vector, and b is a scalar. The position of the separating hyperplane is defined by vector W and the scalar b.

Table 2. Advantages and Disadvantages of Common Machine Learning Models

Model	Strength	Weakness
GA	Effective for global optimisation, complex problems, and feature selection.	Slow convergence, computationally expensive, and sensitive to parameter tuning, with a risk of local optima.
1D-DCNN	Designed for time-series data with effective temporal pattern learning and automatic feature extraction.	Requires large training data, prone to overfitting on small datasets, and computationally expensive for long sequences.
FCNN	Combines fuzzy logic with CNN for handling uncertainty, providing interpretable outputs and strong performance in pattern recognition.	More complex architecture requires more resources and may underperform in simple contexts without uncertainty.
CNN	Feature extraction is efficient for big data	Long-time training, High computing cost,
MPL	Simple architecture and easy to implement	Prone to overfitting without enough data or regularisation
SVM	Low storage and high accuracy	Slow computing for big data, noise-sensitive
GA	Effective for global optimisation, complex problems, and feature selection.	Slow convergence, computationally expensive, and sensitive to parameter tuning, with a risk of local optima.
1D-DCNN	Designed for time-series data with effective temporal pattern learning and automatic feature extraction.	Requires large training data, prone to overfitting on small datasets, and computationally expensive for long sequences.
FCNN	Combines fuzzy logic with CNN for handling uncertainty, providing interpretable outputs and strong performance in pattern recognition.	More complex architecture requires more resources and may underperform in simple contexts without uncertainty.

7. Results and Discussion

Considerable performance disparities. GA obtained 95% accuracy in Laith S. Sawaqed & Ayman M. Alrayes (2020), demonstrating excellent optimization outcomes. Oliver Mey et al. (2020) achieved 98.6% accuracy with FCNN, exhibiting exceptional performance in processing fuzzy data. SeonWoo Lee et al. (2021) used the MFCC and STFT approaches to obtain 99.5%, demonstrating the potential of time-frequency analysis. Feature extraction algorithms such as PCA, t-SNE, ISOMAP, ICA, and AE produced variable results, with AE reaching 97.45%. Salman Yusuf Ibrahim et al. (2023) found that

Random Forest, KNN, and CatBoost had lesser accuracy than others (71.45%, 66.61%, and 89.5%). In Xiaopeng Liu et al. (2023), 1D-DCNN achieved a notable 99% accuracy, while ResNet-3N reached 99.23% in Muhammad Wisal & Ki-Yong Oh (2023).

Ardalan F. Khalil and Sarkawt Rostam (2024) reported a moderate SVM performance of 93.24%. Finally, Vijyalakshmi K et al. (2024) found that MLP and CNN outperformed traditional models by 90% and 95%, respectively, demonstrating an ongoing trend, as shown in Table (3) and Figure (6).

Table 3. Various Machine Learning Algorithms' Performance

References	Model	Average accuracy (%)
Laith S. Sawaqed & Ayman M. Alrayes, 2020 [38]	GA	95%
Oliver Mey, Willi Neudeck, et al.,2020 [39]	FCNN	6%.98
SeonWoo Leea, Yu-Hyeon Tak, et al., 2021 [21]	MFCC and STFT	99.5%
Lucas Costa Brito , Gian Antonio Susto, et al., 2021[26]	PCA, t-SNE ISOMAP ICA AE	97.45% 96.67% 87.14% 97.39 % 81.32%
Salman Yusuf IBRAHIM & M. A. ILYAS ,et al., 2023[22]	Random Forest, KNN, CatBoost	71.45% 66.61% 89.5%
Xiaopeng Liu, Jianfeng Hong ,et al., 2023[23]	1D-DCNN	99%
Muhammad Wisal & Ki-Yong Oh, 2023[30]	ResNet-3N	99.23%
Ardalan F. Khalil & Sarkawt Rostam, 2024[40]	SVM	93.24%
Vijyalakshmi K ,Amuthakkannan Rajakannu, et al., 2024[25]	MLP CNN	90% 95%

Previous studies faced some challenges in implementing machine learning for fault diagnosis. One major issue is that sufficient data is required to train more complex models, as it is difficult to deal with real, inconsistent, and noisy data. To improve accuracy and reliability, more detailed models are needed to function properly with various sources and operating conditions. It needs real processors and sufficient memory to collect and analyze data in real time, relying on advanced equipment and modern techniques to monitor and diagnose faults. However, it is difficult to obtain data on actual faults due to the risk of machine downtime or breakdown. Lastly, relying on supervised learning methods is impractical in the absence of data that includes all faults.

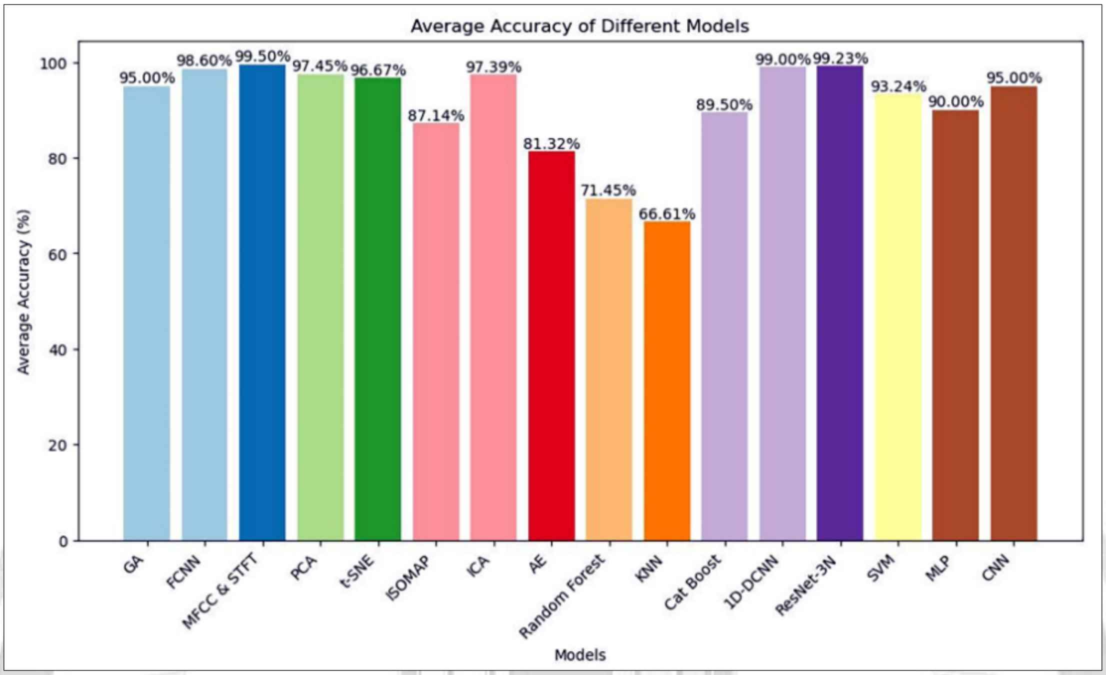

Figure 6. Performance comparison of machine learning algorithms

8. Conclusion

This research provides a comprehensive study on machine learning (ML) methods and the application of maintenance strategies, particularly predictive maintenance, in industrial facilities. The following are the research's basic findings:

- The ability of predictive maintenance to reduce machine breakdowns and thus maintain operational continuity.

Predictive maintenance contributes to reducing the cost of production by reducing wasted expenses on maintenance strategies currently in place in the facility, and reducing the volume of unnecessary spare parts purchases, and increasing performance levels through continuous and real monitoring of the various parameters of the machine and its surrounding environment.

Many different techniques are available to implement the new approach, so decision-makers and technicians in the facility have several options in determining which technique to use, depending on the type of machine and its breakdowns (mechanical, electrical, lubrication) in addition to cost consideration.

ML algorithms such as CNN and 1D-DCNN may distinguish minute changes in data such as vibrations and temperature, allowing defects to be detected before they cause a disastrous breakdown.

ML algorithms can adjust to changes in machine circumstances, which increases their ability to adapt to defect prediction.

ML algorithms can recognize complicated correlations in data, allowing for accurate problem identification even in an incomprehensible failure occurrence.

ML algorithms can be used in systems that monitor in real-time to enable continuous fault detection and reduce unexpected downtime.

ML algorithms on human expertise for fault diagnosis, leading to more consistent and reliable results.

ML algorithms enable proactive maintenance scheduling based on fault predictions, improving resource allocation and reducing unnecessary inspections.

Future work should be to adopt supervised and unsupervised learning methods to improve fault detection. Developing an integrated diagnostic system using advanced devices and modern technologies to include detection, identification, prediction, and location, or by creating models specific to each component to determine the type of fault, to reduce complexity. To ensure the sustainable operation of rotating equipment, it is necessary to focus on predictive maintenance and expand models to monitor and evaluate the condition of equipment at the highest level, not just at the level of an individual failure. Lastly, the reduction of data volume while maintaining the predictive performance of the model is achieved by enhancing preprocessing algorithms.

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مراجعة شاملة لخوارزميات التعلم الآلي لتشخيص الأعطال والتنبؤ بها في المكائن الدوارة

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الخلاصة:

أظهرت خوارزميات التعلم الآلي أهمية كبيرة في كشف الأعطال والصيانة التنبؤية للمعدات الصناعية، ممايحسن من الكفاءة ويقلل التوقف المفاجئ. تستخدم نماذج مثل CNN وSVM وMLP لتحليل بيانات المستشعرات وتصنيف الأعطال، مع تقنيات معالجة الإشارات لاستخلاص الخصائص الهامة. تستخدم طرق تقليل الأبعاد مثلPCA وAutoencodersلتبسيط البيانات المعقدة وكشف الإشارات الدالة على الأعطال.

وأثبتت نماذج التعلم العميق مثل 1D-DCNN وResNet-3N فعاليتها في فهم الأنماط الزمنية وتحسين دقة التنبؤ بالأعطال.

الكلمات الدالة: – التعلم الآلي، تحليل الاهتزازات، الآلات الدوارة، اكتشاف الأعطال.