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Estimating Faults in Electric Motors Using Bearing Vibration with Deep Learning

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Abstract : Electric motors are devices that convert electrical energy into mechanical energy, which are essential across industries, including HVAC systems, home appliances, electric vehicles, robotics, aerospace, and renewable energy systems. However, they are prone to faults and vulnerable to damage from factors like excessive Voltage fluctuations, Bearing Vibrations, Overloading, Overheating, etc., Early fault detection is crucial to prevent costly downtime and repairs. In past technologies, deep recurrent and convolutional neural networks (NNs) with residual connections are empirically evaluated for their feasibility in predicting latent high-dynamic temperatures continuously inside permanent magnet synchronous motors (PMSMs) due to their high torque. While effective, it has limitations in generalizing across different motors and requires a large dataset for transfer learning. This study presents a methodology for detecting motor faults, focusing on analyzing bearing vibrations. A non-contact vibration pickup system captures data from rotating machinery, aiding in early fault detection. The system uses the Hilbert transform for denoising, Principal Component Analysis (PCA), Heterogeneous Sensing Data Fusion for dimensionality reduction, and Sequential Floating Forward Selection (SFFS) for feature selection. Machine learning techniques, specifically Support Vector Machines (SVM) and Artificial Neural Networks (ANN) are employed for fault classification. The proposed system not only facilitates timely fault detection by comparing the machine learning techniques of ANN and SVM which achieves an accuracy of 86.6% and 81.3% respectively, but also offers substantial savings in time, effort, and maintenance costs, thereby enhancing industrial operations' overall reliability and efficiency.

KEYWORDS: Non- contact Bearing Vibration, Fault Prediction, Artificial Neural Network (ANN), Permanent Magnet Synchronous Motors (PMSMs), Sequential Floating Forward Selection (SFFS), Heterogeneous Sensing Data Fusion.

I. INTRODUCTION

The integration of Internet of Things (IoT) technology has ushered in a new era of interconnectedness, enabling diverse sensors to communicate seamlessly in various environments. However, this connectivity also presents challenges, particularly in predicting failures within IoT systems [5] due to the complexity of data sources. To address these challenges, this study leverages Artificial Neural Network (ANN) models, known for their ability to effectively manage and fuse imprecise information from diverse sensing sources within the IoT framework.

1.1 Deep Learning

Deep learning is significantly impacting the field of electrical industries, offering transformative solutions across various domains [13]. Machine learning, one key application is in fault detection and diagnosis, where machine learning algorithms analyze electrical signals to identify anomalies in power systems, enhancing reliability and reducing downtime.

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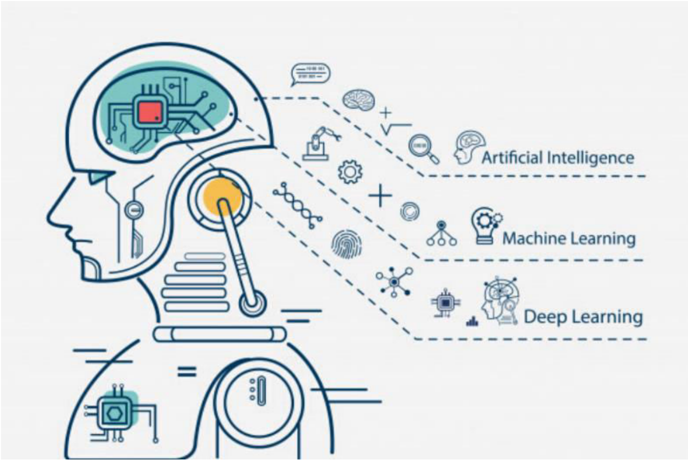

Figure 1. Deep Learning

1.2 Fault Prediction

Fault prediction is a key component in the field of system reliability and performance optimization that has the potential to transform preventive maintenance techniques, Figure 2.

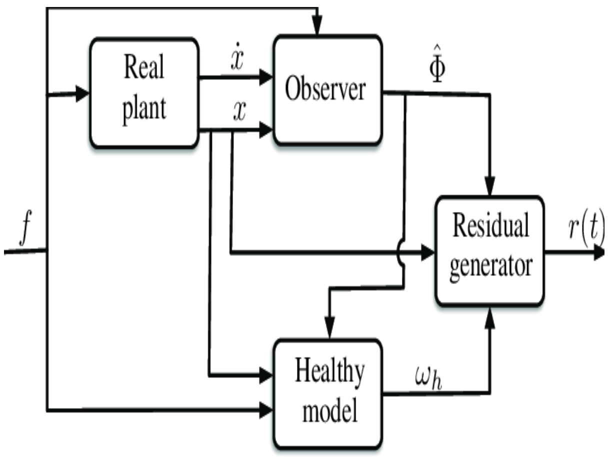

Figure 2. Fault Prediction

By proactively identifying possible flaws or abnormalities in a system before they become serious problems, this predictive technique helps to minimize downtime and avert catastrophic failures ultimately in electrical drives [6].

1.3 Heterogeneous Sensing Data Fusion

The process of integrating, and synthesizing data from various and divergent sensors to provide a more thorough precise knowledge of a particular environment or system is known as heterogeneous sensing data fusion, see Figure 3.

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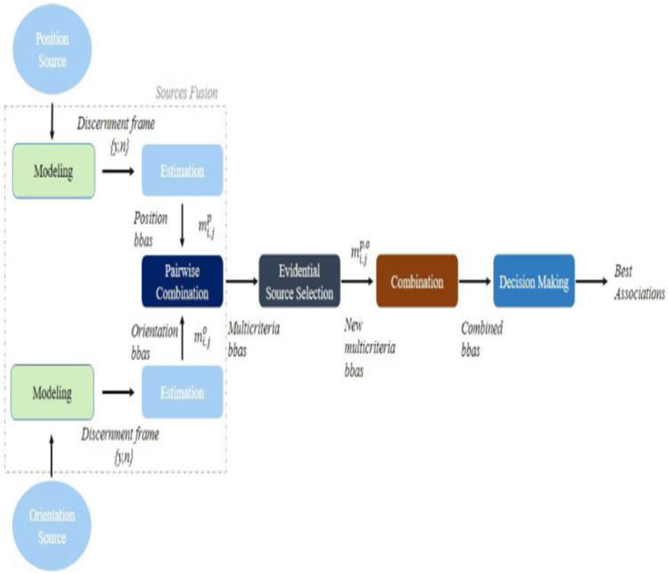

Figure 3. Heterogeneous Sensing Data Fusion

Heterogeneous data fusion is necessary to capture a fuller and more complex picture of the underlying phenomena in circumstances where numerous kinds of sensors are deployed, each with varied modalities, resolutions, and sensing principles. To produce a cohesive and coherent image, this procedure entails merging data from sources like image sensors, audio sensors, heat sensors, and more.

III. LITERATURE SURVEY

2.1 Sensorless rotor temperature estimation of Permanent Magnet Synchronous Motor

The proposed method for estimating the temperature of PMSM presented by M. Ganchev, C. Kral, H. Oberguggenberger, and T. Wolbank [1] exploits the d-axis saturation effects in the steel stator core by intermittently injecting a voltage pulse in the d-axis of the motor. This results in a d-current response that is dependent on both the initial value of the d-current and the magnetization level of the magnets. The variation in the magnetization level of the permanent magnets, caused by temperature changes, is reflected in the variation of the d-current slope upon the voltage pulse. By analyzing this relationship, the method can estimate the temperature of the permanent magnets without the need for temperature sensors. Experimental validation of the method is demonstrated on surface permanent-magnet motors, showing promising results. The method provides a temperature-sensorless and robust technique for estimating the temperature of permanent magnets in PMSM, offering a novel approach to temperature estimation in electric machines.

2.2 A systematic study of the class imbalance problem in convolutional neural networks

Oliver Wallscheid, Tobias Huber, Wilhelm Peters, and Joachim Böcker [2] present a review of state-of-the-art model-based methods for determining the magnet temperature in PMSM. Since direct measurement of magnet temperature is often not feasible, this review categorizes existing publications into thermal models, flux observers, and voltage signal injection approaches. Virtual sensor fusion approaches, for example, could enable reciprocal plausibility checks within the determination techniques. In conclusion, this paper proposes using invasive methods to initialize the state variables of the thermal network after the device starts. They also suggest using fusion structures like Kalman filters or neural networks to merge information from independent approaches for improved estimation accuracy. Additionally, they mention a previous study where a Kalman filter was used to increase estimation accuracy for stator temperatures, although rotor temperatures were not considered.

2.3 Deep Residual Convolutional and Recurrent Neural Networks for Temperature Estimation in Permanent Magnet Synchronous Motors

This study by W. Kirchgässner, O. Wallscheid, and J. Böcker,[3] has addressed the challenge of accurate temperature monitoring using PMSMs. Traditional thermal modeling approaches, lumped-parameter thermal networks (LPTNs), are commonly used to estimate internal component temperatures. However, these methods require expertise in selecting model parameters. To address these challenges, the authors propose the use of deep recurrent and convolutional

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neural networks (RNNs and CNNs) with residual connections. The study focuses on a highly utilized PMSM for electric vehicle applications, modeling the temperature profile in various components such as the stator teeth, winding, yoke, and rotor's permanent magnets. The results show that the deep RNNs and CNNs with residual connections achieve mean squared error and maximum absolute deviation performances comparable to LPTNs.

2.4 Thermal Monitoring of Electric Motors: State-of-the-Art Review and Future Challenges

Oliver Wallscheid [4] proposes that Monitoring temperature in electric motors is crucial for protecting components from overheating while maximizing power and torque capabilities. This paper focuses on indirect methods, which track temperature-sensitive electrical motor parameters, and direct methods, including lumped-parameter thermal networks and supervised machine learning. However, maintaining safe operating temperatures is crucial, as thermal overloading can lead to increased wear and motor failures. Accurately determining the motor's thermal state is essential for minimizing safety margins related to temperature. While a thermal analysis during the motor design phase may suffice for simple applications with stable conditions, dynamic applications like vehicle traction or automation require continuous monitoring to prevent thermal overloading.

2.5 Digital Twin-Based Monitoring System of Induction Motors Using IoT Sensors and Thermo-Magnetic Finite Element Analysis

Jhennifer f. Dos santos, bendict k. Tshoombe, Lucas H. B. Santos, Ramon c. F. Araújo, Allan r. A. Manito, wellington s. Fonseca, and marcelo o. Silva [5] has introduced a predictive maintenance tool for electric motors using Digital Twin (DT) and Industrial Internet of Things (IIoT) concepts. The system monitors motor current and temperature using sensors and a low-cost acquisition module, transmitting measurements via Wi-Fi to a database. The DT concept is employed by feeding measurements into a high-fidelity model of the motor, created using the Finite Element Method (FEM). Computer simulations reveal relative errors below 4% in conductivity analysis and 10% in temperature analysis. The proposed system was tested on an induction motor in a controlled environment, with commercial sensors installed for comparison. The system's measurements of phase current and temperature closely matched those of the commercial sensors, with relative errors under 10%.

IV. EXISTING SYSTEM

3.1 Neural Network

The majority of traction drive applications lack accurate temperature monitoring capabilities [3], requiring expensive large motor designs to ensure safe operation. Furthermore, their primary benefit over data-driven techniques [8], physical interpretability, deteriorates when their degrees of freedom are reduced to satisfy the real-time requirements. In this paper, deep recurrent and convolutional neural networks (NNs) [11] are tested for their ability to forecast high-dynamic temperatures constantly inside PMSM. The temperature profile of the stator teeth, winding, and yoke, as well as the rotor's permanent magnets, are approximated here, with ground truth accessible as test bench data.

3.2 Temporal convolutional Networks

Temporal convolutional networks (TCNs) have emerged as a powerful alternative to recurrent neural networks (RNNs) in sequential learning tasks. Causality ensures that TCNs only consider past observations, Dilation refers to the spacing between receptive fields of a filter, allowing TCNs to capture events further in the past. Despite having shared weights, TCNs reduce the total number of trainable parameters compared to equivalent fully connected feedforward neural networks (FNNs) [7], [9].

Additionally, TCNs do not maintain inner memory cells like RNNs [3], simplifying their architecture. Residual connections, inspired by the concept of skip connections in residual networks, further enhance the performance of TCNs. Lean models with good estimation performance at small model sizes are given using an automated hyperparameter search via Bayesian optimization and a manual merging of target estimators into a multi-head architecture.

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V. PROPOSED SYSTEM

The suggested system acquires data from spinning machinery using a non-contact vibration pickup, allowing for early failure diagnosis in bearings.

Table 1. Pseudocode for the entire process

PSEUDOCODE:

Input: BearingFaultDataset

Output: Comparison of both classifiers of ANN and SVM

Begin

Load the dataset

Use the Hilbert transform for denoising the dataset

Split the dataset into training (80%) and testing (20%)

For Feature Selection *Apply* PCA for feature extraction and normalization

Select the 18 most important features using the SFFS algorithm

Train the SVM classifier using the selected features

Use the selected features for testing the SVM classifier

Calculate accuracy, precision, recall, F-measure, and execution time for SVM

For training the ANN classifier using the selected features

Use the selected features for testing the ANN classifier

Calculate accuracy, precision, recall, F-measure, and execution time for ANN

Compare the results of both SVM and ANN classifications.

End

1.3 Load Bearing Fault Dataset

The project focuses on obtaining and curating a comprehensive dataset especially specialized to load-bearing problems in rotating machinery in this module. This entails gathering vibration data under various load situations.

Table 2. Dataset details

Dataset Description:

Dataset Name: BearingFault Dataset

Source: UCI repo Kaggle

Number of Rows: 1001

Number of Columns: 264

Training Set: 80% - 997 rows, 264 columns

Testing Set: 20% - 49 rows, 254 columns

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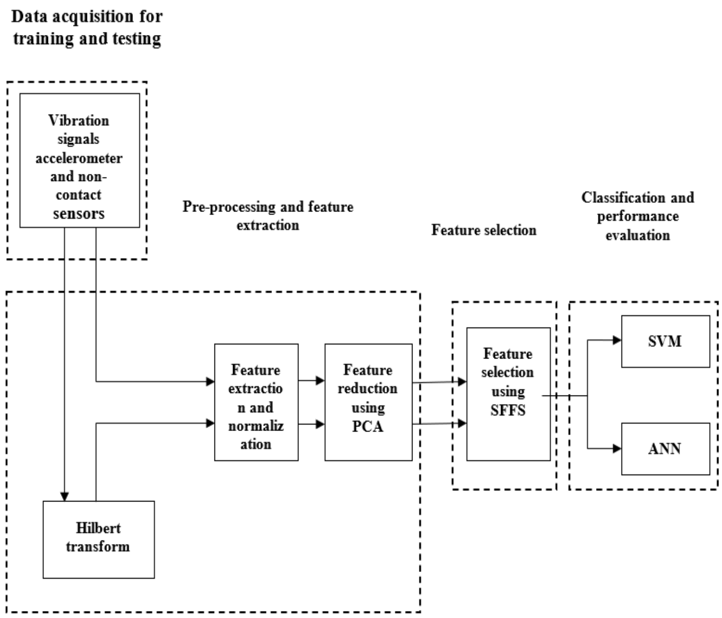

Figure 4. Block Diagram

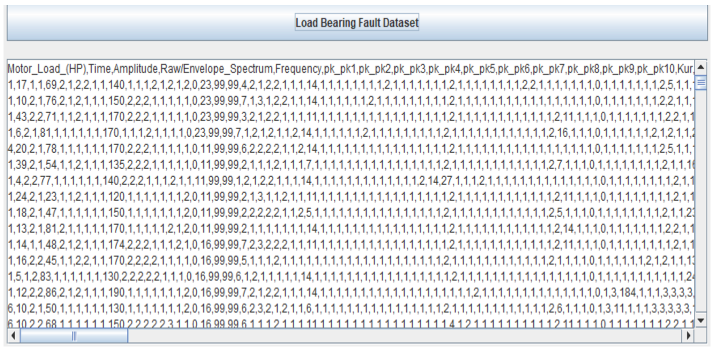

Figure 5. Load BearingFault Dataset

4.2 Feature reduction using PCA based on feature extraction and normalization

PCA is used to minimize the dimensionality of a dataset by calculating the Pearson correlation coefficient and normalization while maintaining crucial information and reducing the danger of overfitting.

4.2.1 Pearson Correlation Coefficient for Feature Extraction and Normalization

This Pearson correlation formulation is used to calculate the correlation matrix. This correlation matrix provides important insights into the relationships between the variables in the dataset. The correlation matrix helps identify which variables are strongly correlated, which can affect the selection of principal components and the interpretation of the results.

The Formula is:

$$r_{xy} = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \quad (1)$$

Where:

r_{xy} is the Pearson correlation coefficient between variables x and y, x_i , and y_i are the individual data points, $\bar{x}$ and $\bar{y}$ are the means of variables x and y respectively, and n is the number of data points.

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The Normalization formula is:

$$z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \qquad (2)$$

Where:

$x = (x_1, x_2..., x_n)$ and z_i is ith normalized data.

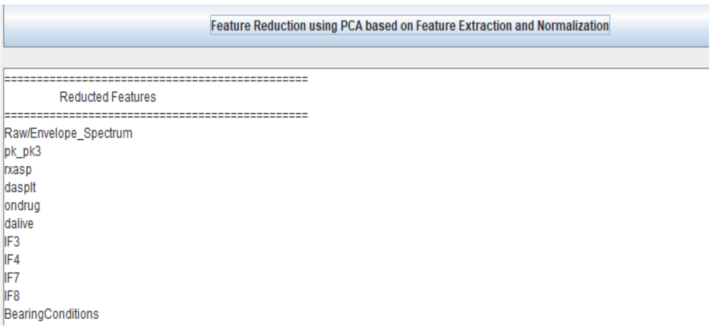

Figure 6. Feature Reduction using PCA

The below Table.1 shows the values of reduced features and their integer-related scores after extracting the attributes by performing Principal Component Analysis.

Table 3. Scores of Reducted Features

S. No	Reducted Features	Score (int)
1	Time	0.5
2	Raw/Envelope Spectrum	0.5
3	Frequency	0.6
4	pk_pk3	0.7
5	rdate	0.5
6	hourlocal	0.5
7	minlocal	0.6
8	daylocal	0..5
9	rxasp	0.5
10	dasplt	0.6
11	ondrug	0.8
12	dalive	0.5
13	IF3	0.8

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14	IF4	0.7
15	IF7	1.0
16	IF8	1.0
17	Skew1	0.6

4.3 SVM based on feature selection using SFFS Algorithm

Sequential Floating Forward Selection (SFFS) is used to enhance feature selection in a Support Vector Machine, a strategy that iteratively discovers and adds the most discriminative features to improve the model's performance.

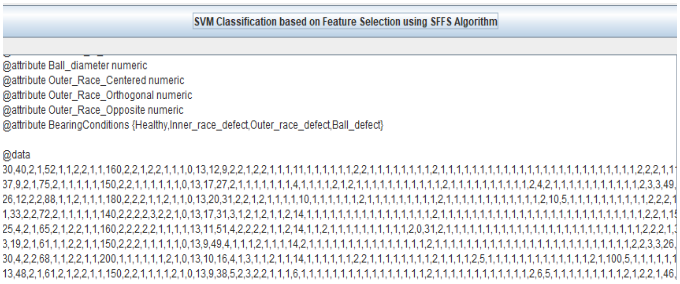

Figure 7. SVM based on SFFS

4.4 ANN classification based on feature selection using SFFS

The research uses Artificial Neural Networks (ANN) [11] based on SFFS in addition to comparing the results of Support Vector Machines (SVM) to classify bearing failures.

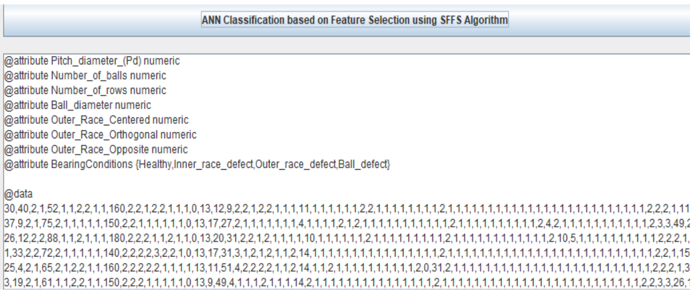

Figure 8. ANN based on SFFS

The formula for calculating Accuracy, Recall, Precision, and F- Measure are calculated:

Accuracy:

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100$$

Precision:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives}+\text{False Positives}}$$

Recall (Sensitivity or True Positive Rate):

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives}+\text{False Negatives}}$$

F-measure (Harmonic Mean of Precision and Recall):

$$\text{F-measure} = \frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}}$$

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VI. RESULT ANALYSIS

The following table showcases the accuracy, recall, precision, F-Measure, and execution time. The comparison between the two algorithms is shown and undoubtedly ANN proves its performance very well on the above metrics than the SVM.

Table 4. Comparison Table

Algorithm	Accuracy	Precision	Recall	F-measure	Execution Time
SVM	0.813	0.857	0.816	0.731	0.08
ANN	0.866	0.985	0.942	0.846	0.1

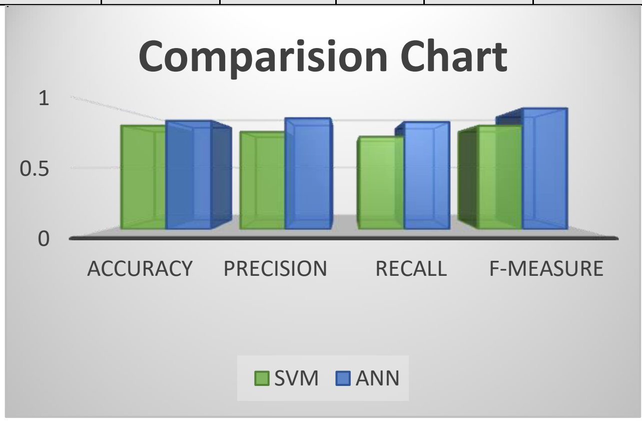

Figure 9.1 Comparison graph

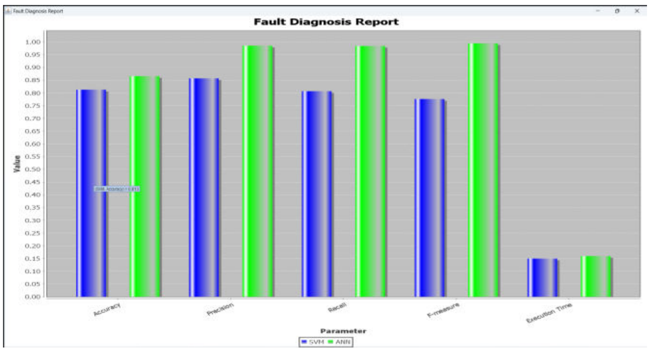

Figure 9.2 Comparison graph

5.1 Support Vector Machine

The comparison Table. 3 provides the insight of SVM algorithm's total accuracy of 81.3% is impressive, indicating that it can accurately categorize examples. Recall, which gauges the algorithm's capacity to record all relevant occurrences, is stated at 85.7%, while the precision, which shows the algorithm's ability to prevent false positives, is at 81.6%. At 73.1%, the F-measure is computed, offering a fair evaluation of recall and accuracy. Also, the execution time of the SVM is Obtain at 0.08.

5.2 Artificial Neural Network

The ANN algorithm's excellent capacity to prevent false positives is shown by its 86.6% accuracy, and its efficacy in identifying relevant occurrences is demonstrated by its 94.2% recall rate and the precision rate is obtained at 98.5%. Significantly, the ANN's F-measure stands out at 84.6%, highlighting the algorithm's well-balanced performance between accuracy and recall. The ultimate rate of execution time is 0.1 in ANN.

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VIII. CONCLUSION AND OUTLOOK

Finally, the created non-contact vibration pickup, along with modern data processing and machine learning approaches, has shown to be a reliable and practical method for monitoring bearing health in rotating machinery. The effective deployment of SVM and ANN algorithms illustrates the system's capacity to detect faults in real-time with the utmost percentage in ANN. This shows us that ANN performs better than any other machine learning algorithms in the industry. This complete technique not only improves the proactive nature of maintenance procedures, but also offers significant savings in time, resources, and equipment upkeep expenses.

Future work must investigate and enhance the suggested system to fit a greater range of industrial environments and machinery types. Further research into the non-contact vibration pickup's flexibility across diverse operational circumstances and settings will increase the system's versatility. Incorporating real-time monitoring capabilities and investigating the incorporation of future technologies like as edge computing or the Internet of Things might also give a more dynamic and responsive approach to bearing health monitoring. Continuous research efforts should be directed toward optimizing machine learning algorithms, with the possibility of adding deep learning models for enhanced pattern identification and fault detection.

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