Centrifugal Pump Fault Diagnosis using a Predictive Maintenance Model

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Abstract

With the increasing focus on process automation and the advent of Industry 4.0, predictive maintenance strategies (PdM) have gained significant attention. These strategies enable maintenance actions to be performed when necessary, reducing downtime costs and enhancing the efficiency and availability of production machinery. The widespread adoption of advanced analytical tools and Machine Learning (ML) technologies has facilitated continuous monitoring of machine operation through the development of PdM models. In this study, we propose an ML-based approach to develop a prediction model specifically for the manufacturing sector. The model employs supervised learning, utilizing the sliding window method and the Support Vector Machine algorithm (SVM), reaching an accuracy of 99.7%. By leveraging artificial intelligence for predictive maintenance, our algorithm enables the monitoring of a centrifugal pump using acoustic and vibration parameters. This enables the identification and prediction of five distinct operating conditions of the pump.

Keywords
Predictive Maintenance, Machine Learning, centrifugal pump, manufacturing sector, sliding window

1. Introduction
Maintenance is a complex activity that involves various actions and strategies. Corrective Maintenance, for instance, involves taking action only after a breakdown or failure has already occurred. While this type of maintenance initially incurs no costs, it can have a significant impact on a company by causing longed production interruptions.
On the other hand, Preventive Maintenance is performed proactively, aiming to prevent machine damage by conducting scheduled work based on predetermined time intervals or asset usage intensity. This strategy offers advantages such as improved work organization, efficient downtime management, and process optimization. However, it also results in increased maintenance costs, which may not always be strictly necessary or cost-effective.
Predictive maintenance is a proactive strategy that involves continuously monitoring operational parameters like vibration, temperature, energy consumption, fluid levels, and others to analyze machine conditions and predict future failures. By implementing predictive maintenance, productivity can be increased, costs can be optimized, and unnecessary interventions can be avoided. This strategy effectively mitigates problems and risks associated with potential breakdowns and production interruptions.

Among the various machines used in production, the centrifugal pump holds significant industrial applications, ranging from food processing to water and sewage transportation. It is a commonly used pump in various industries and is liable to failures caused by issues within the fluid, such as cavitation, as well as mechanical faults in components like bearings and seals. Vibration monitoring is a suitable method for identifying faults within pumps. To prevent damage to these machines, relevant sensor data can be utilized to monitor their condition and develop an efficient maintenance strategy (McKee K. et al. 2011).

In recent years, the utilization of Artificial Intelligence (AI) algorithms in predictive maintenance techniques has significantly advanced the capabilities of maintenance engineers. These algorithms enable engineers to analyze sensor data, identify anomalies, and schedule interventions before a machine failure occurs. By investigating complex phenomena and determining the optimal timing for maintenance actions, predictive maintenance techniques have garnered considerable interest. This approach not only predicts potential failures but also assesses the consequences of neglecting specific interventions, yielding substantial results with relatively modest investments.

Machine Learning (ML) techniques have been instrumental in enabling predictive maintenance by utilizing sensor data. These techniques offer benefits such as cost and production time reductions, as well as improvements in workplace safety (Carvalho et al. 2019). ML algorithms apply mathematical-computational methods to input information and continually improve their performance as they learn from increasing data sets in an adaptive manner. The objective of this study is to investigate the predictability of machine failures by simultaneously analysing two sets of parameters, namely acoustic and vibration data, which are characteristic of a centrifugal pump motor. A novel methodology has been developed based on ML techniques, which analyze data from both acoustic and vibration sensors to assess the machine's status, determine the need for predictive maintenance, identify the appropriate type of operation, and indicate the specific type of impending failure among the five configurations. These AI-based techniques enable effective and efficient equipment monitoring, thereby minimizing costs and reducing downtime during maintenance activities.

The structure of the paper is as follows: Section 2 presents a literature review, followed by Section 3, which describes the methodology employed. Section 4 provides details on the conducted case study, while Section 5 discusses the obtained results. Finally, Section 6 concludes the work, highlighting the main limitations and suggesting future directions for further research.

2. Literature review

Several authors have explored the application of Machine Learning (ML) techniques in the field of predictive maintenance. For instance, Mallouk et al. (2021) developed a supervised learning-based prediction model to estimate the remaining mileage of truck tires used for transporting hazardous substances, comparing different regression algorithms. Fernandes et al. (2020) employed ML algorithms to predict boiler failures up to seven days in advance. Calabrese et al. (2020) utilized a predictive maintenance approach to simultaneously screen multiple connected machines, leveraging insights from terabytes of log data.

DeShong et al. (2022) applied ML techniques to estimate changes in local film cooling rates by analyzing surface temperature measurements on rotating turbine blades. Tan et al. (2022) presented an Ensemble Learning approach combined with Multiscale Retinex with Color Restoration (IMSRCR) and You Only Look Once (YOLO) systems to detect corroded bolts using image data captured inside tunnels. Chung et al. (2023) focused on performing uptime predictions for semiconductor manufacturing equipment based on inspection data and maintenance reports, effectively classifying failures. Nuhu et al. (2023) implemented ML-based techniques for fault diagnosis in the semiconductor manufacturing process.

Yuan et al. (2023) proposed the use of the Support Vector Machine (SVM) algorithm for fault detection in a molecular pump. Sridevi and Bothra (2022) presented a predictive maintenance model specifically for lead-acid batteries, utilizing ML algorithms.

Furthermore, ML applications for damage detection in centrifugal pumps have shown significant relevance. Mousmoulis et al. (2017) investigated the process of cavitation in centrifugal pumps, analyzing flow images, vibrations, and acoustic emissions from three different impellers. Their results demonstrated the feasibility of detecting cavitation onset using an acoustic emission sensor and an accelerometer. Gao et al. (2019) conducted a study on rapid fault diagnosis in axial piston pumps, employing vibration analysis and a hybrid approach of Walsh transform denoising and Teager energy operator (TEO) demodulation.

Gonçalves et al. (2021) conducted an assessment of cavitation failures in a centrifugal pump by utilizing Markov parameters derived from vibration data as features in classification algorithms based on convex optimization.
Azadeh et al. (2013) proposed a flexible algorithm for classifying pump conditions, employing support vector machine hyperparameter optimization and artificial neural networks. Their study demonstrated that the support vector classifier performance improved when incorporating a hybrid model with a genetic algorithm and particle swarm optimization.
Hasan et al. (2021) presented a framework for automated health diagnosis of a centrifugal pump. Their approach involved a continuous wavelet transform (CWT) scalogram-based imaging technique combined with an adaptive deep convolutional neural network (ADCNN).

Manikandan et al. (2023) focused on vibration-based fault diagnosis in industrial mono-block centrifugal pumps. They collected vibration signals related to three configurations: a healthy pump, a pump with a broken impeller, and a pump with seal failure. Converting the analog signals into 2D images, they employed deep convolutional neural network (DCNN) classifiers to predict failures, achieving an accuracy of 99.07%.

Orrù et al. (2020) presented a preliminary ML model analyzing real historical data from temperature, pressure, and vibration probes mounted on a centrifugal pump in the oil and gas sector. They employed Support Vector Machine (SVM) and Multilayer Perceptron (MP) algorithms to recognize and classify potential faults.
Yen et al. (2020) analyzed historical vibration data from pumps using a WaveNet-based autoencoder to determine their degradation.

Kumar et al. (2020) utilized acoustic data in the same dataset to detect pump defects using ML and Deep Learning methods. With ML, they achieved accuracies of 93% with SVM, 86.4% with ANN, and 84.8% with ANFIS. Employing deep learning systems, they obtained an accuracy of 96.8% with a conventional CNN and 100% with an improved CNN by modifying the cost function.

Considering the existing literature, there are limited studies addressing predictive maintenance and artificial intelligence specifically incorporating both vibration and acoustic data. Thus, this study aims to analyze both acoustic and vibration data to predict potential failures in pump impellers or bearings within the manufacturing sector.

3. Research questions and methodology

ML, a subset of Artificial Intelligence, enables computer systems to learn from experience and improve their performance over time. By providing the machine with data sets and processing them using specific algorithms, ML allows the system to develop a logic that performs a function to achieve a specific objective. ML algorithms can be applied to various tasks such as classification, clustering, transcription, machine translation, and anomaly detection.
In the context of predictive maintenance, ML methods offer promising solutions to prevent equipment failures in production lines. They can uncover complex relationships within data that may be challenging to capture using traditional tools. ML enables the detection of impending failures and provides more accurate predictions about the state of a machine (Wagner et al. 2016).

The research methodology for this study comprises four distinct steps, as illustrated in Figure 1.

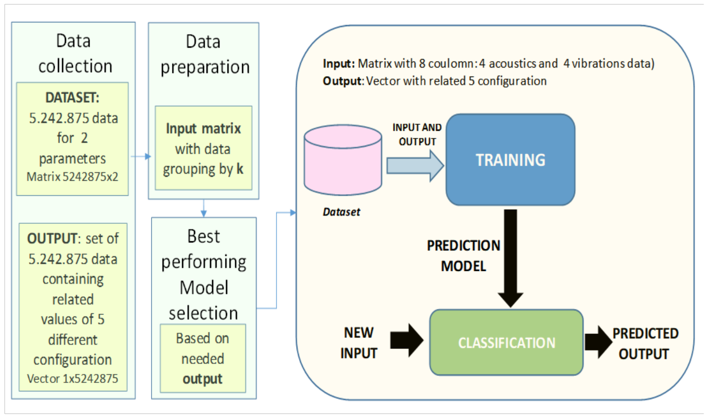

Figure 1. The fault prediction process based on multinomial classification

1. Data collection: The dataset used in this study was obtained from the IEEE scientific data platform, specifically from Anil Kumar and Rajesh Kumar (2022).
2. Data preparation: Before conducting the analysis, the raw dataset requires preprocessing due to missing information, large text data, and unorganized or noisy data. To address these issues, various pre-processing activities are performed. In this case study, the sliding windows method is utilized to improve accuracy, latency, and processing costs. The sliding window approach involves moving a window of a specified length over the data, sample by sample, and conducting statistical analyses on the data within each window. The window length determines the length of data used for calculating statistics. Finding the optimal size for the sliding window parameter (k) is crucial for achieving optimal results. In this study, several evaluations are conducted using five different values for the parameter k.
3. Selection of the best performing model: The study employs machine learning (ML) techniques that involve two learning methods, as described by Rao et al. (2019):
   - Unsupervised learning: This technique aims to identify hidden patterns or unknown classes in the input data. It is suitable for datasets without labeled responses, and clustering is a common approach within unsupervised learning.
   - Supervised learning: This method uses known input and output data to build a model that can predict future outputs based on new inputs. Supervised learning encompasses two main techniques:
     - Classification: This technique predicts discrete responses by grouping input data into categories.
     - Regression: This approach predicts continuous responses and is used when the expected response is a real number.

The choice of algorithm depends on the specific problem at hand, as there is no universally optimal ML algorithm for all scenarios. In this case study, the predictive analysis employs supervised learning with classification, using the algorithms listed in Table I.

In this way, it is possible to obtain as output the classification that represents the state of the pump, based on the input data entered.

Training and evaluation of the chosen classification model: The datasets are split into three components: Training set, this set is utilized to train the predictor until it attains satisfactory performance levels; Validation set, during the training process, this set is employed to validate the model's performance; Test set, the final evaluation of the predictive model is conducted using this set, which consists of real-world data to which the model has not been previously exposed. It allows for an assessment of the model's end-to-end performance. The evaluation involves using appropriate metrics derived from the Confusion Matrix, such as accuracy and ROC. The developed research methodology can be applied to the predictive phase, enabling the reliable and efficient diagnosis of failures in centrifugal pumps

Table I. Selected algorithms and default value for parameters

TESTED ALGORITHM	Parameters	Default Value
Support Vector Machines	C	1
	kernel	rbf
	coef0	0
Discriminant Analysis	priors	none
	n_components	none
	tol	1.0e-4
Naive Bayes Classifiers	priors	none
	var_smoothing	1E-09
Decision Trees	n_estimators	100
	criterion	gini
	max_depth	None
Nearest NeighborClassifiers	n_neighbors	5
	radius	1.0
	algorithm	auto
	leaf_size	30

Case Study

The validation of the methodology involves the utilization of a CRI brand monoblock centrifugal pump, specifically the ACM-0 (AF) model, operating at a speed of 43 Hz, as depicted in Figure 2. The pump is powered by a voltage of 230/240V and is driven by a motor with a power output of 373 Watts. It has a discharge rate of 1.61 liters per second and operates at a head of 9 meters. The pump comprises three rotating impellers with a diameter of 119 mm.
The pump is positioned on a test bench, as shown in Figure 1, which consists of a rotor rotating on two bearings. The bearing located closest to the impeller is identified by the model number 6203ZZ. It has a pitch circle diameter of 28.5 mm, a ball diameter of 6.74 mm, and is equipped with eight balls, with a contact angle of 0°.

Sensors and Data acquisition device

To capture the vibration and acoustic data generated by the pump motor, two sensors positioned on the test bench are employed. These sensors are connected to a portable data acquisition device. For acoustic data collection, a microphone (ECM8000) is utilized, while vibration data is detected using a uniaxial accelerometer (PCB 353B34). The chosen data acquisition device is the NI-USB-4431, which is a 24-bit, 4-channel analog I/O device specifically designed for data acquisition purposes. The vibration signal is captured at a sampling frequency of 70 kHz. The device features four input channels capable of detecting voltage signals within the ±10 V range.

Figure 2. Test rig

Dataset and fault model of the pump

The experiments are conducted in 5 different configurations, shown in Table 2:

Table 2. Analysed configurations

N	CONDITION OF PUMP
1	Defect free
2	Broken impeller (BI)
3	Clogged impeller (CI)
4	Bearing with inner race defect (IR)
5	Bearing with outer race defect (OR)

For each of the configurations, 1048575 measurements are determined, both with the acoustic sensor and with the vibration sensor. The sampling frequency adopted is 70,000 samples per second. Datasets containing such data are made available by Anil Kumar and Rajesh Kumar, (2022). In total, 1048575x5 beeps and 1048575x5 vibration signals are provided.

Data processing

During the preprocessing stage, a sliding window method is employed. The acoustic data corresponding to each of the five pump conditions (no defects, broken impeller, clogged impeller, bearing with internal position defect, and external raceway defect) are grouped based on a parameter "k." For each group of "k" items, the mean, minimum, maximum, and standard deviation are calculated. This process is repeated for various values of "k," selected based on the sampling frequency of 70,000 samples per second. The same procedure is applied to the vibration data.
Subsequently, the obtained data for each "k" value are organized into a matrix consisting of nine columns. The first four columns (1 to 4) display the average, maximum, minimum, and standard deviation values obtained by grouping the acoustic sensor data for the five configurations (1 for pump without defects, 2 for broken impeller, 3 for clogged impeller, 4 for bearing with inner race defect, and 5 for bearing with outer race defect) in the specified order. The subsequent four columns (5 to 8) display the average, maximum, minimum, and standard deviation values obtained by grouping the vibration sensor data in the same order. Column 9 contains the data corresponding to the respective configuration, as indicated in Table 1.

Table 3. presents the selected "k" values and the dimensions of the matrices obtained from the corresponding data processing steps.

Table 3. . Obtained matrix for different k values

k VALUES	SIZE OF THE OBTAINED MATRIX	TOTAL NUMBER OF SAMPLE	TOTAL NUMBER OF SAMPLE FOR EACH HEALTH CONDITION
70	74900X9	74900	14980
100	52430X9	52430	10486
700	7490X9	7490	1498
1000	5245X9	5245	1049
1500	3500x9	3500	700

Choose of best performing Model

Each of the five matrices obtained with different values of "k" is utilized for predictive analysis using machine learning (ML) techniques. The chosen technique for this analysis is classification, as the objective is to predict the presence or absence of a fault in the centrifugal pump based on its vibration and acoustic data and classify it into one of the categories listed in Table 1.

For each of the five matrices, various algorithms are tested. These include Decision Tree, Discriminant Analysis, Nearest Neighbor Classifiers, Kernel Approximation Classifiers, and Ensemble Classifiers. The performance of each algorithm is evaluated in terms of accuracy. The accuracy values obtained for each algorithm and matrix are determined, and the best performances achieved for each matrix are documented.
Table 4 shows obtained best accuracy value and related algorithm, for different values of k.

Table 4. Best five results against k and the chosen algorithm

k VALUES	BEST TESTED ALGORITHM	ACCURACY
70	Decision Tree	81,3
100	Support Vector Machines	90
700	Support Vector Machines	98,2
1000	Support Vector Machines	99,1
1500	Support Vector Machines	99,7

From table 4, it is possible to see that best result (accuracy of 99,7) is obtained for k=1500 using Support Vector Machine (SVM) algorithm.
For this value of k forecast analyses are performed with various algorithms. Table 5. shows the accuracy results obtained with the different algorithms analyzed on the matrix with k=1500.

Table 5. Results with different algorithms for k=1500

TESTED ALGORITHM	MAX ACCURACY RESULT (%)
Support Vector Machines	99,7
Discriminant Analysis	99,4
Naive Bayes Classifiers	99,3
Decision Trees	99
Nearest NeighborClassifiers	98,8

The training process is conducted by processing 39000obs/sec with a total training time of 2.255 sec. The model used is the Medium Gaussian SVM characterized by a Kernel function of Gaussian type with a scale of 2.8 and box constraint level of 1. The Multiclass method used has been One-vs-one. Cross-validation (CV) is also used to obtain a more reliable estimate of the assessment metrics. CV divides the overall dataset in K_{CV} separate folds (K_{CV}=5) and metrics are evaluated on each fold.

As shown in Figure 3, 75% of dataset was used for Training set, 15% for Validation set and 15% for Test set.

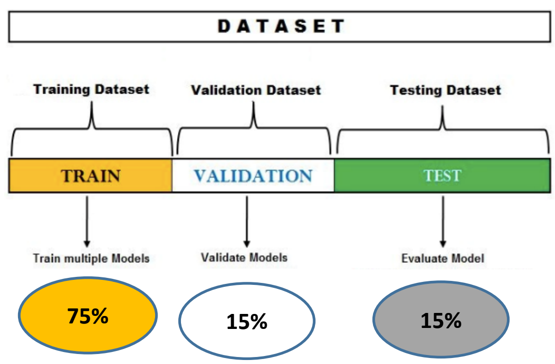

Figure 3. Dataset partitioning for training, validation and test

5. Result and Discussions

The application of ML techniques using a classifier has yielded remarkable results with simple and fast methods that require low computing power. By employing the sliding window method for data preprocessing and utilizing the Medium Gaussian Support Vector Machine (SVM) ML algorithm, an excellent accuracy of 99.7% is achieved.

The developed system enables the prediction of the centrifugal pump's status, indicating specific conditions such as:

- Good condition (Class 1)
- Broken impeller (Class 2)
- Clogged impeller (Class 3)
- Bearing with inner race defect (Class 4)
- Bearing with outer race defect (Class 5)

The obtained confusion matrix is depicted in Figure 4, while Figure 5 illustrates the Receiver Operating Characteristic (ROC) curve. These visual representations provide further insight into the performance and effectiveness of the predictive model.

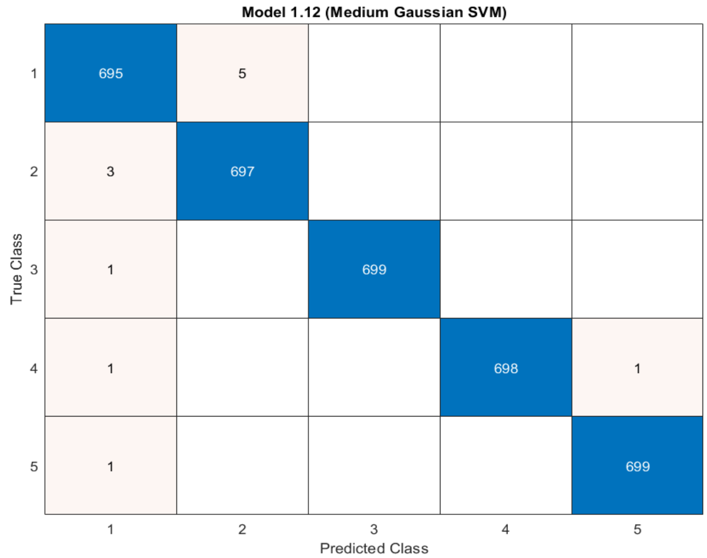

Figure 4. Confusion Matrix

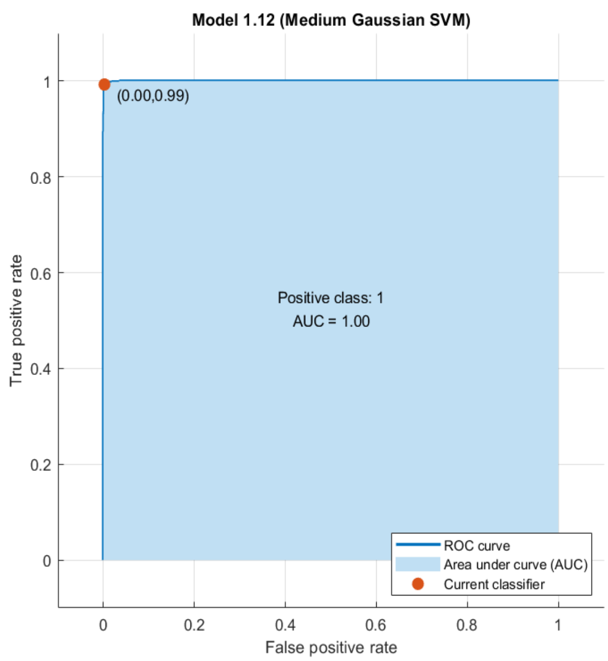

Figure 5. Curve ROC

Figure 6 shows the results obtained, divided into 5 classes while Table 6 reports Positive Prediction Values (PPV) and False Discovery Rates (FDR) of the proposed model, divided for the 5 classes (no defects, broken impeller, clogged impeller, bearing with internal position defect and bearing with external position).

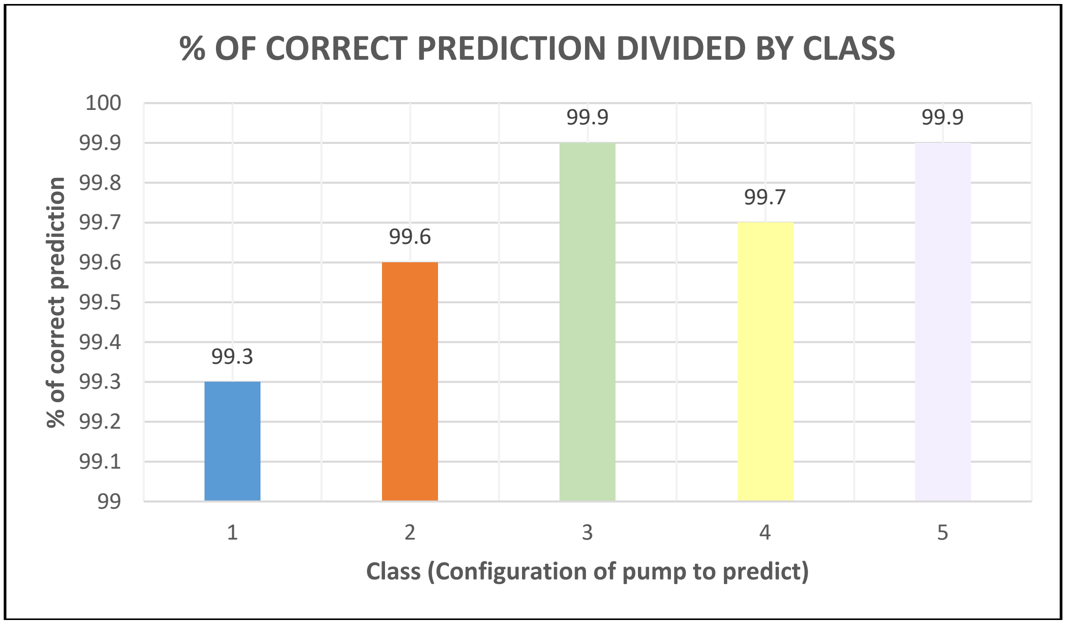

Figure 6. Correct prediction percentage divided into 5 Classes

Table 6. . PPV and FDR values divided by class

	PPV	FDR
Class1	99,10%	0,90%
Class2	99,30%	0,70%
Class3	100,00%	0,00%
Class4	100,00%	0,00%
Class5	99,90%	0,10%

Class 1 scored a slightly lower performance with prediction errors of 0.9%, and it had the highest False Discovery Rate values among all the classes.

The results obtained in this study, utilizing appropriate pre-processing with the sliding window method and ML techniques, have demonstrated excellent predictive capabilities with higher accuracy values (99.7% accuracy) compared to the previous forecasting models proposed by Kumar et al. (2020) in all cases except for the improved CNN model with a modified cost function, which achieved a 0.3% higher accuracy. However, the improved CNN model is more complex, resource-intensive, and requires longer training times compared to the SVM model proposed in this study. Therefore, the proposed solution is more effective and efficient.

6. Conclusions

This study focuses on developing a predictive model for a centrifugal pump, aiming to assess its condition and predict the type of fault using ML techniques. The experimental datasets used in this study include acoustic and vibrational

data collected from a test bench. The sliding window method is employed for data preprocessing, and the chosen prediction algorithm is SVM. The obtained results demonstrate excellent accuracy levels (99.7%), highlighting the effectiveness and efficiency of the methodologies used, which also have cost advantages over deep learning-based methods.
For future studies, it would be beneficial to optimize the prediction performance for class 1, which obtained lower accuracy values, by exploring more specific ensemble algorithms. Additionally, the application of the developed predictor in real maintenance scenarios could be evaluated, considering cost analysis. Furthermore, regression models could be applied to the vibrational and acoustic data to determine the residual useful life (RUL) of the centrifugal pump, offering valuable insights for maintenance planning.

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