Predictive maintenance model for fault diagnosis on centrifugal pumps

M. Menanno and A. Salsano [a)]

a. Dipartimento di Ingegneria, University of Sannio, Piazza Roma, 21 82100 – Benevento – Italy (marialuisa.menanno@unisannio.it, anita.salsano@unisannio.it)

Abstract: Nowadays the growing interest in process automation and the emergence of Industry 4.0 are leading to greater attention to predictive maintenance strategies (PdM) that allow to perform maintenance actions when necessary, reducing costs of downtimes and increasing the efficiency and availability of production machines. The progressive diffusion of advanced analytical tools and Machine Learning (ML) technologies allows us to constantly monitor the operating status of the machines by developing PdM models. In this work an ML approach is proposed to develop a prediction model in the manufacturing sector based on supervised learning by applying the sliding window method and using the Support Vector Machine algorithm (SVM), reaching an accuracy of 99.7%. This algorithm, based on artificial intelligence for predictive maintenance, is applied to monitor a centrifugal pump based on acoustic and vibration parameters and allows the identification and the prediction of the occurrence of five different operating conditions of the pump.

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

I. INTRODUCTION

Maintenance is a complex activity involving several actions and different strategies. In Corrective Maintenance, action is taken only after a breakdown or failure has occurred. This type of maintenance has no initial costs but can cause a huge impact on the company by halting production for a considerable time in case of a failure. Preventive Maintenance is carried out before the breakdown to prevent the machine from damage and involves carrying out work according to a schedule, usually established based on the time or intensity of use of a given asset. This type of maintenance strategy brings advantages, such as better organization of work, efficient downtime management, and process optimization. But it also involves an increase in maintenance costs, which become more severe and not always strictly necessary. Predictive maintenance is a proactive strategy with the aim of analyzing machine conditions by constantly monitoring operational parameters such as vibration, temperature, energy consumption, fluid levels, etc. to predict future failures. Predictive maintenance thus increases productivity and optimizes costs, avoiding unnecessary interventions while preventing problems and risks related to possible breakdowns and production interruptions.

There are several machines used in production; the centrifugal pump, which has a wide range of applications (from food processing to the transport of water or sewage transportation) certainly finds many industrial applications. It is a common pump used in industry, and it usually fails due to problems occurring within the fluid, such as cavitation, and mechanical faults, also found in bearings and seals. Vibration monitoring is suitable for determining faults within pumps. To prevent damage to this machine, data from suitable sensors can be used to monitor its condition and create an effective maintenance strategy [1].

In recent years, predictive maintenance techniques have increasingly benefited from the use of Artificial Intelligence algorithms, which helps maintenance engineers to analyze data from sensors, identify anomalies, and to schedule intervention before an anomaly occurs that stops the machine. The datasets are used to investigate a phenomenon that is difficult to model and to predict when it is more appropriate to intervene with maintenance actions on the machinery. This application is arousing growing interest because, with a relatively modest outlay, it is possible to achieve great results, not only predicting the occurrence of a failure but also what could happen in the absence of a specific intervention.

The use of Machine Learning (ML) techniques allows predictive maintenance using data gathered from sensors, achieving cost and production time reductions and workplace safety improvements [2]. ML algorithms apply mathematical-computational methods to input information, improving their

performance in an 'adaptive' way as the data set from which they learn increases.
The purpose of this study is to investigate whether machine failure can be predicted by considering the simultaneous analysis of two sets of parameters (acoustic and vibration data) characteristic of a centrifugal pump motor.
A new methodology has been developed, starting from ML techniques, and analyzing the data from the two sensors (acoustic and vibration), to establish the status of the machine, identify whether predictive maintenance is required and the type of operation to be performed, also indicating the type of failure about to occur considering the five configurations. These techniques, which belong to the AI, provide equipment monitoring to perform an effective and efficient maintenance activity, minimizing costs and downtime.
The paper is organized as follows. After the literature review (section 2), section 3 describes the methodology used. Section 4 details the case study conducted. Section 5 discusses the results obtained, while Section 6 concludes the work with its main limitations and future directions of the study.

II. LITERATURE REVIEW

Different authors have applied ML to predictive maintenance. [3] propose an ML approach to develop a prediction model based on supervised learning comparing different regression algorithms, applied to the prediction of the remaining mileage of truck tires used to transport hazardous substances. [4] used ML algorithms to predict failures in boilers up to 7 days before they occur. [5] used a predictive maintenance approach to enable simultaneous screening of multiple connected machines by learning from terabytes of log data. [6] used ML techniques to estimate changes in local film cooling rate using the surface temperature measured on the pressure side of a rotating turbine blade. [7] presented an Ensemble Learning approach combined with a Multiscale Retinex with Color Restoration (IMSRCR) and You Only Look Once (YOLO) system that analyses image data inside tunnels to detect corroded bolts. [8] classified failures by performing uptime predictions based on inspection data and maintenance reports of semiconductor manufacturing equipment. [9] implemented machine learning-based techniques for fault diagnosis in the semiconductor manufacturing process.
[10] proposed the use of the Support Vector Machine (SVM) algorithm for fault detection in a molecular pump. [11] presents a predictive maintenance model for lead-acid batteries using ML algorithms.
Furthermore, the applications of ML for damage detection in the centrifugal pump are certainly relevant. [12] investigates the process of cavitation of a centrifugal pump analyzing flow images and measurements of vibrations and acoustic emissions with three different impellers. The results show that it is possible to detect the onset of cavitation via an acoustic emission sensor and an accelerometer. [13] presents a study on rapid fault diagnosis in axial piston pumps based on vibration analysis using a hybrid method of Walsh transform denoising and Teager energy operator (TEO) demodulation.
[14] assess cavitation failures in a centrifugal pump using Markov parameters from vibration data as features in classification algorithms based on convex optimization.
[15] proposed a flexible algorithm for classifying the condition of pumps based on the optimization of support vector machine hyperparameters and artificial neural networks. Furthermore, the result showed that the support vector classifier improves when applying a hybrid model with a genetic algorithm and particle swarm optimization.
[16] presents a framework for automated health diagnosis of a centrifugal pump based on a continuous wavelet transform (CWT) scalogram-based imaging technique combined with an adaptive deep convolutional neural network (ADCNN).
A vibration-based fault diagnosis in industrial mono-block centrifugal pumps is presented in this study. An experimental configuration for structuring databases, required for developing algorithms for running ML programs, is designed. Standard condition vibration signals are collected from the setup when the pump is healthy and free of defects. This study considers the two major defective conditions of broken impeller (B.I.) and seal failure (S.F.).
[17] uses vibrations for the diagnosis of block centrifugal pumps. The vibration signals are related to 3 configurations (pump without defects, with broken impeller and broken seal). The collected analog signals are then converted into 2D images and deep convolutional neural network (DCNN) classifiers are used to predict failures, obtaining an accuracy of 99.07%.
[18] presents a preliminary ML model that analyzes real historical data detected by temperature, pressure, and vibration probes mounted on a centrifugal pump used in the oil and gas sector through two algorithms Support Vector Machine

(SVM) and the Multilayer Perceptron (MP), to recognize and classify potential faults.
[19] analyzes historical vibration data on pumps to determine their degradation using a WaveNet-based autoencoder.
[20] used the acoustic data contained in the same dataset to detect pump defects with ML and Deep Learning methods; with ML authors have achieved an accuracy of 93% with SVM, 86.4% with ANN, and 84.8% with ANFIS. Moreover, using deep learning systems (conventional CNN) they have obtained a value of accuracy of 96,8 while using an improved CNN modifying cost function achieving 100%.
Based on the extant body of literature, few studies address predictive maintenance and artificial intelligence considering vibration and acoustic data. Therefore, this study analyzes both acoustic and vibration data together to predict potential failures on the pump impeller or bearings in the manufacturing sector.

III. RESEARCH FRAMEWORK

ML is a type of Artificial Intelligence that allows the computer system to learn from experience to improve performance after completing a task. Learning is achieved by providing the machine with data sets that, processed through specific algorithms, allow the definition of the logic to perform a function aimed at a specific objective. Many types of tasks can be solved with ML algorithms such as classification, clustering, transcription, machine translation, and anomaly detection problems.
ML methods are also promising tool in predictive maintenance applications and are used to prevent failures in production line equipment. Indeed, through ML it is possible to determine the complex relationships in the data that could be difficult to capture with common tools, to detect incoming failures, and to determine a greater precision in predicting the state of a machine [21].
The research methodology is divided into four steps (see Figure 1).

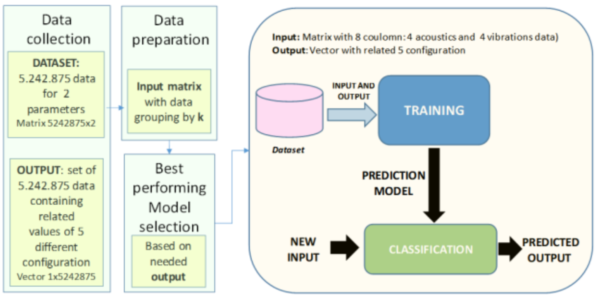

Figure 1. Framework

1) *Data collection*: the database is acquired on IEEE scientific data platform by Anil Kumar and Rajesh Kumar, (2022).

2) *Data Preparation*: the available dataset cannot be used as is to perform the analysis process, as it lacks some information, extremely large text data, and unorganized or noisy data. It is necessary to perform pre-processing activities. In this case study, the sliding windows method is used to verify improvement in accuracy, latency, and cost of processing. In the sliding window method, a window of a specified length moves over the data, sample by sample, and statistical analyses are performed on the data in each window. The window length defines the data length over which the algorithm calculates the statistics. It is important to research the optimal size of the sliding window (k) to optimize the results. In our case, several evaluations with five different dimensions of the parameter k are considered.

3) *Selection of best performing model*: ML uses two learning techniques [22]:

● unsupervised, which finds hidden patterns or unknown classes in the input data. It is used on input datasets with no labeled responses. Clustering is the most common unsupervised learning technique.

● supervised, which uses known input and output data to define a model which is then used to predict future outputs in response to new inputs. Supervised learning uses techniques from:

○ classification, which predicts discrete responses. Classification models group input data into categories;

○ regression, which predicts continuous responses. This technique is used if the expected response is a real number.

The choice of the algorithm also depends on the specific problem: no ML algorithm is optimal for all models. In this case study the predictive analysis is performed using supervised learning with classification, through algorithms shown 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.
4) Training and evaluation of the selected classification model: the datasets are divided into 3 parts: 1) Training set, used to train the predictor until it achieves satisfactory performance; 2) Validation set: to validate the model during the training process; 3) Test set: to evaluate the predictive model's final end-to-end performance on real-world data to which the model has never been

exposed. The model is assessed using appropriate metrics derived from the Confusion Matrix (accuracy and ROC).

TABLE I. SELECTED ALGORITHMS AND DEFAULT VALUE FOR PARAMETERS

Testes 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 Neighbor Classifiers	n_neighbors	5
	radius	1.0
	algorithm	auto
	leaf_size	30

The research methodology developed can be used for the predictive phase to diagnose centrifugal pump failures reliably and efficiently.

IV. CASE STUDY

Validation of the methodology is performed using a CRI brand monoblock centrifugal pump (model: ACM-0 (AF)) operating at a speed of 43 Hz (see Figure 2). The pump is powered by a voltage of 230/240V and is driven by a motor that has a power of 373 Watts. The pump discharge is 1,61 liter/sec at the head of 9 m. There is a closer impeller with three rotating impellers and a diameter of 119 mm. The pump is placed on a test bench (shown in Figure 1), consisting of a rotor rotating on 2 bearings. The bearing closest to the impeller has the model number 6203ZZ; it has a Pitch circle diameter of 28,5 mm, a ball diameter of 6.74 m, and 8 balls, with a contact angle of 0°.

A. Sensors and Data acquisition device

For the acquisition of the vibration and acoustic data produced by the pump motor, two sensors placed on the test bench are used, both of which are connected to a portable data acquisition device. Acoustic data acquisition is performed using a microphone (ECM8000) while a uniaxial accelerometer (PCB 353B34) has been used for Vibration data detection. The Data acquisition device used is a NI-USB-4431. It is a 24-bit, 4-channel analog I/O device used to acquire the vibration data. The signal is acquired at a sampling frequency of 70kHz. The device has four input channels for detecting voltage signals in the range of ±10 V.

Figure 2. Test rig

B. Dataset and fault model of the pump

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

TABLE II. 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.

C. *Data processing*

The produced dataset is analyzed and preprocessed to remove errors and inconsistences and reshape data layout in a format suitable for feeding prediction models.

In this pre-processing phase, a sliding window method is used: the acoustic data relating to each of the 5 different pump conditions (no defects, broken impeller, clogged impeller, bearing with internal position defect, and external raceway defect) are grouped according to a parameter k. For each of these k-item groupings, the mean, minimum, maximum, and standard deviation are determined. Several calculations are carried out for different values of k, chosen based on the sampling frequency of 70,000 samples per second. The operation is repeated in the same way also for the vibration data.

Subsequently, for each value of k, the data obtained are grouped in a matrix made up of 9 columns. The first 4 columns (from 1 to 4) show the average, max, min, and standard deviation values calculated by grouping by k the data detected by the acoustic sensors of the 5 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- placed in this succession. The following 4 columns (from 4 to 8) show the average, max, min, and standard deviation values calculated by grouping the data detected by the vibration sensors by k, always placed in the same succession. Column 9 shows the data corresponding to the relative configuration according to numbers indicated in Table 1.

Table III shows the selected values of k and the dimensions of the matrices obtained from the related processing.

TABLE III. OBTAINED MATRIX FOR DIFFERENT K VALUES

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

D. *Choose of best performing Model*

Each of the five obtained matrices, with different values of k, is used for forecasting analysis with ML techniques. In particular, the classification technique is chosen because the purpose is to determine the algorithm, which allows predicting the presence or absence of a fault in the centrifugal pump starting from its vibration and acoustic data, classifying the situation in one of the cases listed in table 1.

Different algorithms are tested for each of the 5 matrices obtained as k varied. In particular: Decision tree, Discriminant analysis, Nearest neighbor classifiers, Kernel approximation classifiers, and Ensemble classifiers.

In all cases, the accuracy values are determined, and the best performances obtained for each matrix are reported in Table IV.

TABLE IV. ACCURACY FOR DIFFERENT K VALUES

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 IV it is possible to see that for k=1500 an accuracy of 99,7 is obtained.

For this value of k forecast analyses are performed with various algorithms. Table V shows the accuracy results obtained with the different algorithms analyzed on the matrix with k=1500.

TABLE V. RESULTS WITH DIFFERENT ALGORITHMS FOR K=1500

TESTED ALGORITHM	MAX ACCURACY RESULT (%)
Support Vector Machines	99,7
Discriminant Analysis	99,4
Naive Bayes	99,3
Decision Trees	99
Nearest Neighbor	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.

V. RESULTS AND DISCUSSIONS

The use of ML techniques via classifier has achieved excellent results with simple and fast methods and low computing power. In particular, by pre-processing the data with the sliding window method and using the Medium Gaussian SVM ML algorithm, excellent accuracy values are obtained (99,7%).

The system created allows predicting the status of the centrifugal pump indicating the pump conditions specifically if the pump is:

- in 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).

Figure 3 shows the confusion matrix while Figure 4 shows the ROC diagram.

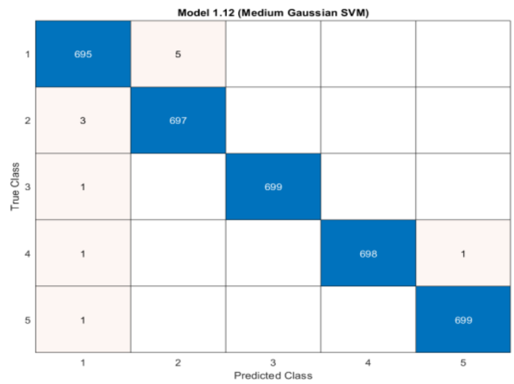

Figure 3. Confusion Matrix

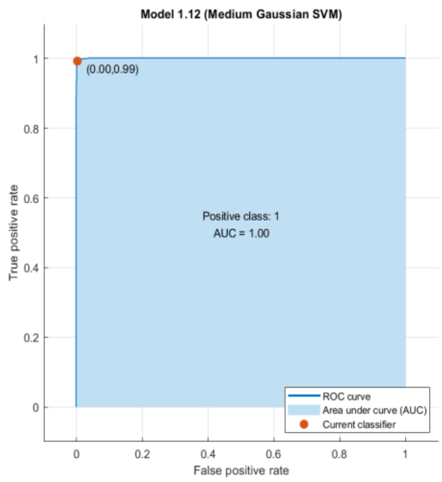

Figure 4. Curve ROC

Table VI shows the results obtained, divided by class while Table VII 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).

TABLE VI. RESULTS DIVIDED BY CLASS

CLASS	% OF CORRECT PREDICTION
1	99,3
2	99,6
3	99,9
4	99,7
5	99,9
Overall	99,7

TABLE VII. 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 slightly lower with prediction errors of 0.9% and the highest False Discovery Rate values occurred precisely in this class.

The results obtained in the present study through an appropriate pre-processing with the sliding window method and the application of ML techniques have allowed to obtain excellent predictions with higher accuracy values (99.7% accuracy) compared to the previous forecasting models of Kumar et al., (2020) in all cases [20], except for the improved CNN modifying cost function model, which achieved 0.3% higher accuracy, but is certainly more complex, demanding and hence requires longer training times than the SVM model proposed in this study. Therefore, the proposed solution is more effective and streamlined.

VI. CONCLUSIONS

In this study, a predictive model is built on a centrifugal pump. The approach evaluates the state of the machine and predicts the type of fault considering the 5 configurations using the ML technique based on experimental datasets containing acoustic and vibrational data, detected on a test bench. The sliding window method is used in the data preprocessing phase while the chosen prediction algorithm is SVM. The results obtained showed excellent levels of accuracy (99.7), using effective and efficient methodologies that have a positive effect on costs than other deep learning-based methods.

Future studies could optimize the performance of predictions in class 1 that have obtained lower accuracy values using more specific ensemble algorithms.

Another future application of this work can be oriented to evaluate the impact using the predictor in real maintenance scenarios with cost analysis evaluation.

In addition, regression models could be applied to vibrational and acoustic data to determine the residual useful life (RUL) of the centrifugal pump.

VII. REFERENCES

[1] McKee K., Forbes G., Mazhar M. I., Entwistle R., Howard. I. (2011). "A review of major centrifugal pump failure modes with application to the water supply and sewerage industries". In ICOMS Asset Management Conference Proceedings. Asset Management Council.

[2] Carvalho, T. P., Soares, F. A., Vita, R., Francisco, R. D. P., Basto, J. P., & Alcalá, S. G. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. Computers & Industrial Engineering, 137, 106024.

[3] Mallouk, I., Sallez, Y., & Abou El Majd, B. (2021, May). Machine learning approach for predictive maintenance of transport systems. In 2021 Third International Conference on Transportation and Smart Technologies (TST) (pp. 96-100). IEEE.

[4] Fernandes, S., Antunes, M., Santiago, A. R., Barraca, J. P., Gomes, D., & Aguiar, R. L. (2020). Forecasting appliances failures: A machine-learning approach to predictive maintenance. Information, 11(4), 208.

[5] Calabrese, M., M. Cimmino, F. Fiume, M. Manfrin, L. Romeo, S. Ceccacci, M. Paolanti, G. Toscano, G. Ciandrini, and A. Carrotta. 2020. SOPHIA: An Event-Based IoT and Machine Learning Architecture for Predictive Maintenance in Industry 4.0. Information ed. Vol. 11(4):2020.

[6] DeShong, E. T., Berdanier, R. A., & Thole, K. A. (2022). Predictive Modelling of Local Film-Cooling Flow on a Turbine Rotor Blade. In Turbo Expo: Power for Land, Sea, and Air (Vol. 86038, p. V06AT12A027). American Society of Mechanical Engineers.

[7] Tan, Lei, Tao Tang, and Dajun Yuan. (2022). An Ensemble Learning Aided Computer Vision Method with Advanced Color Enhancement for Corroded Bolt Detection in Tunnels. Sensors. 22(24), 9715.

[8] Chung, E., Park, K., & Kang, P. (2023). Fault classification and timing prediction based on shipment inspection data and maintenance reports for semiconductor manufacturing equipment. Computers & Industrial Engineering, 108972.

[9] Nuhu, A. A., Zeeshan, Q., Safaei, B., & Shahzad, M. A. (2023). "Machine learning-based techniques for fault diagnosis in the semiconductor manufacturing process: a comparative study". The Journal of Supercomputing, 79(2), 2031-2081.

[10] Yuan, X. L., Kai, J., Chen, Y., Zuo, G. Z., Zhuang, H. D., Li, J. H., & Hu, J. S. (2023). A support vector machine framework for fault detection in molecular pump. Journal of Nuclear Science and Technology, 60(1), 72-82.

[11] .Sridevi, H. R., & Bothra, S. (2022). Predictive Maintenance of Lead-Acid Batteries Using Machine Learning Algorithms. In Emerging Research in Computing, Information, Communication and Applications: Proceedings of ERCICA 2022 (pp. 729-738). Singapore: Springer Nature Singapore.

[12] Mousmoulis, G., G. Karlsen-Davies, N. Aggidis, J. Anagnostopoulos, and D. Papantonis. (2017). Experimental analysis of the onset and development of cavitation in a centrifugal pump. Journal of Physics: Conference Series Vol. 813, No. 1:p. 012044.

[13] Gao, Q., Tang, H., Xiang, J., Zhong, Y., Ye, S., & Pang, J. (2019). A Walsh transform-based Teager energy operator demodulation method to detect faults in axial piston pumps. Measurement, 134, 293-306.

[14] Gonçalves, J. P. S., Fruett, F., Dalfré Filho, J. G., & Giesbrecht, M. (2021). Faults detection and classification in a centrifugal pump from vibration data using markov parameters. Mechanical Systems and Signal Processing, 158, 107694.

[15] Azadeh, A., Saberi, M., Kazem, A., Ebrahimipour, V., Nourmohammadzadeh, A., & Saberi, Z. (2013). A flexible algorithm for fault diagnosis in a centrifugal pump with corrupted data and noise based on ANN and support vector machine with hyper-parameters optimization. Applied Soft Computing, 13(3), 1478-1485.

[16] Hasan, M. J., Rai, A., Ahmad, Z., & Kim, J. M. (2021). A fault diagnosis framework for centrifugal pumps by scalogram-based imaging and deep learning. IEEE Access, 9, 58052-58066.

[17] Manikandan, S., & Duraivelu, K. (2023). Vibration-based fault diagnosis of broken impeller and mechanical seal failure in industrial mono-block centrifugal pumps using deep convolutional neural network. Journal of Vibration Engineering & Technologies, 11(1), 141-152.

[18] Orrù, P. F., Zoccheddu, A., Sassu, L., Mattia, C., Cozza, R., & Arena, S. (2020). Machine learning approach using MLP and SVM algorithms for the fault prediction of a centrifugal pump in the oil and gas industry. Sustainability, 12(11), 4776.

[19] Yen, F., & Katrib, Z. (2020). WaveNet based Autoencoder Model: Vibration Analysis on Centrifugal Pump for Degradation Estimation. In Annual Conference of the PHM Society (Vol. 12, No. 1, pp. 6-6).

[20] Kumar, A., Gandhi, C. P., Zhou, Y., Kumar, R., & Xiang, J. (2020). Improved deep convolution neural network (CNN) for the identification of defects in the centrifugal pump using acoustic images. Applied Acoustics, 167, 107399.

[21] Wagner, C., Saalmann, P., & Hellingrath, B. (2016). An overview of useful data and analyzing techniques for improved multivariate diagnostics and prognostics in condition-based maintenance. In Annual Conference of the PHM Society (Vol. 8, No. 1).

[22] Rao, J. N., & Ramesh, M. (2019). A Review on Data Mining & Big Data. Machine Learning Techniques. Int. J. Recent Technol. Eng, 7, 914-916.