Jurnal
Teknologi

Full Paper

VIBRATION BASED PREDICTIVE FAULT ANALYSIS OF BEARING SEAL FAILURE AND CAVITATION ON INDUSTRIAL MONOBLOCK CENTRIFUGAL PUMP USING DEEP LEARNING ALGORITHM

Manikandan S[a], Duraivelu K[b]*

[a]Assistant Professor, Department of Mechanical Engineering, Dhaanish Ahmed College of Engineering, Padappai 601301, Chennai, Tamil Nadu, India
[b]Professor, Department of Mechanical Engineering, SRM Institute of Science & Technology, Kattankulathur 603203, Tamil Nadu, India

Article history
Received
14 May 2023
Received in revised form
15 June 2023
Accepted
18 June 2023
Published Online
21 August 2023

*Corresponding author
duraivek1@srmist.edu.in

Graphical abstract

Abstract

Industrial monoblock centrifugal pumps are critical pieces of rotational machinery that play an important role in manufacturing operations. The critical components must be in proper working order for the industry to continue operating. State monitoring is essential for monitoring and analysing the condition of equipment. Bearing failure, cavitation, a broken impeller, and other issues are common in monoblock centrifugal pumps. Traditional procedures for calculating outcomes have been proven to be time-consuming and difficult. At regular intervals, time domain vibrational signals are collected for the defective pump. These vibrational indicators are evaluated to the healthy, defect-free pump. To acquire the accuracy, these images are fed into an efficient deep convolutional neural network (DCNN). This research examines two types of failures outer race bearing seal failure and cavitation. The visuals are trained and assessed in proportions of 70:30. Finally, the DCNN architecture's fault diagnosis accuracy is 99.07%.

Keywords: Cavitation, deep learning algorithm, fault analysis, image processing, signal processing

1.0 INTRODUCTION

A pump is a mechanical component that transmits power from one subsystem to another. It is often used in mechanical transmission, which comprises of plane engines, turbines, pumps and so on. Centrifugal pumps are utilised in a wide range of technical applications in various industries like construction sites, mining activities, mineral extraction, and high stress applications. A minor failure in the pump has devastating consequences, resulting in the breakdown of the entire machine [1]. An industrial monoblock centrifugal pump's impeller and bearing are the two key components that have a direct impact on the pump's [2]. As a result, bearing and impeller problem identification and classification are required to increase centrifugal pump reliability and protection [3]. Vibration data analysis has become a hotspot of signal processing study, and it is crucial for identifying and analysing vibration signals in equipment [4]. Only the outer race defect in bearing seal and the cavitation fault affecting the impeller are examined in this paper.

In aggregate, the four types of fault diagnostic procedures are knowledge-based, model-based, composite approach, and signal-based. The traditional technique to defect diagnosis focuses mostly on frequency characteristics and fault extraction of features [5]. In the past, defect detection technologies relied heavily on processes and different harmonics to resolve an issue [6]. The water pump fault diagnosis predominantly focuses on three factors: i) the primary vibration features from the hydraulic equipment are generally combined with a large amount of extra noise, ii) there is a lack of controller designs capable of generalization, and iii) there is a lack to ensure the effectiveness of the systems development [7]. Because of the functional diversity and complexity of hydraulic systems, fault identification and categorization appear to be more difficult. As the hydraulic system's power source, the hydraulic pump is critical in reflecting the system's operational status. An important research route in rotating equipment fault diagnostics is to employ data-driven signal processing algorithms to assess collect signals and extract significant failure features. These algorithms can react to the data collected and remove critical statistics to assess apparatus condition [8]. Deep learning (DL) based strategies to rotary device fault diagnosis, especially pumps, turbines, and gears, have indeed been extensively used in recent years for more reliable results. The diagnostic capabilities of such freshly developed approaches are stressed in terms of offering notions with the application of revolutionary procedures in rotational equipment [9]. Deep neural networks are a sort of DL technology that learns numerous layers of numerical simulations using both supervised and unsupervised learning [10]. Rather than manually extracting fault features, deep learning approaches can flexibly understand the data structure from original data using various nonlinear transformations and complex nonlinearity functions.

The defect detection process in machines has gained popularity as a result of the successful utilization of deep learning neural networks in the domains of image recognition and language processing [11]. DCNN has sparked a lot of interest in intelligent fault detection, which has also sparked interest in rotary machine fault study [12]. Building a nueral computational model will replicate the human neurological learning process as a specific focused approach of unlabelled data classification. In various research, deep neural networks have proven greater benefits in finding faults organically with much more attributes and showing massive data [13].

An iterative procedure for structuring databases is developed in this field of study as a precondition for developing algorithms for executing machine-learning processes. When the pump is good and free of flaws, normal condition signals are obtained from the setup. Later the vibrational raw data collection is obtained from defective conditions from the equipment. The deficient situations are considered, and signals are obtained. The two major mechanical defects investigated in this study using vibrational signals are outer race defect in bearing and cavitation fault. These signals are converted to 2D images using the image processing technique. It is proposed to use the Deep Convolution Neural Network (DCNN) classifier. Following pre-processing, all samples are divided into 70:30 portions for learning and evaluation [14]. The categorization is then carried out using the deep learning algorithm DCNN, which anticipates the upgraded system based on the preset datasets by utilising different convolution layers, max - pooling, and an activation function rctified linear unit (ReLU). DCNN outperform other standard approaches because they rely largely on recovered features [15]. Eventually, the results are gathered and examined, and the model's fault accuracy is determined.

2.0 METHODOLOGY

The dataset are extracted by vibration signals in the industrial monoblock centrifugal pump (Manikandan and Duraivelu, 2023). The readings are obtained using an accelerometer sensor located between the impeller and motor housing. The most of common general-purpose accelerometer sensors have a strong enough pulse to be tracked without signal disturbances. The information from the sensor is delivered to the computer through the data acquisition unit (DAQ). The vibrational data is sent from the sensor to the DAQ in which the vibrations would be enhanced and filtered. The data of a good monoblock centrifugal pump (GP). The various sensor outputs classify are outer race defect in bearing and cavitation fault. Bearings [16] are indeed a type of rotating component found in a wide range of applications such as compressors, pumps, turbines, engines, and rotors. Excessive pump operation with insufficient preventive maintenance is the leading cause of outer race bearing seal failure. Cavitation is another major hydraulic issue in centrifugal pumps [17], causing increased vibration [18], noise, and a significant loss in pump efficiency. It is induced by a drop in fluid pressure, which results in the formation of air bubbles. Cavitation can lead to impeller blade wear and pitting that can lead to pump failure. Both the outer race bearing seal failure and the cavitation failure are investigated using vibration signals. These signals that will be in the shape of raw data will be processed by utilising Lab VIEW software. MATLAB software will transform the dataset to grayscale image analysis.

In this study, a 0.5 HP rated industrial monoblock centrifugal pump with a flow of 120 LPM, head range 12m to 16.5m, and rating velocity of 2900 rpm is employed. The test rig of a monoblock centrifugal pump is shown in Figure 1. In this research a DAQ NI-9234 data collecting system with a frequency range of 0.5–10000 Hz. 4-channel, 5 V, 51.2 kS/s/channel acquisition unit with 24-bit IEPE signal conditioning and AC coupling is utilized. This study employs an uniaxial accelerometer with a sensitivity of 50 mv/g and a resonance frequency of 40 Hz. The sensor is located close to the motor and impeller housing to collect the amplitude and features.

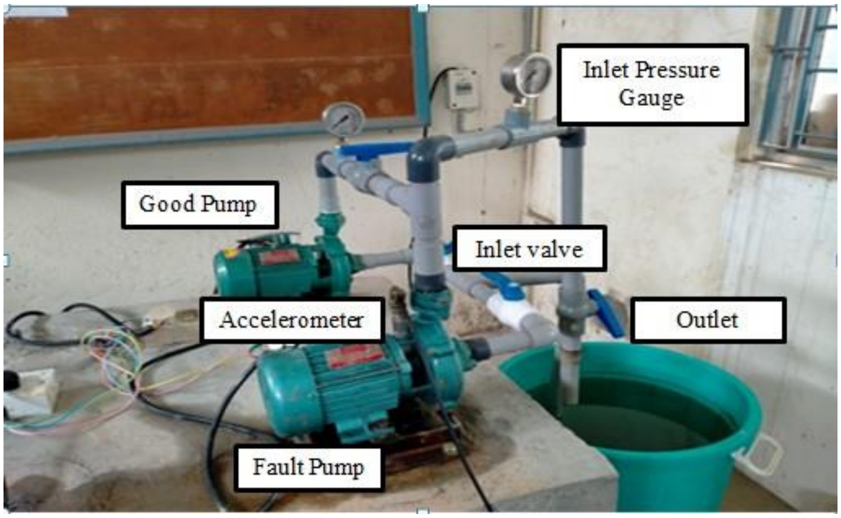


Figure 1 Monoblock centrifugal pump test rig

The two main steps in the process are convolution and pooling. Deep learning [19] approaches arose from the study of artificial neural networks. The DL network is made up of many concealed layers, ranging from tens to dozens. An input image, a max pooling layer, a convolutional layer, a fully connected layer, and an output layer constitutes in DCNN architecture. They are one of the most important and advanced machine learning models, increasing training by pooling and convolutional kernels, which use down sampling to optimise. Convolution receives features from a specified feature map region. The max - pooling is simply a quasi down filtering technique that reduces computation time by lowering system parameters and, to some extent, controls overfitting. In the fully connected layer, a typical feed-forward neural network is used. To resolves the multi-categorisation problem, the proposed DCNN uses the ReLU function as the activation function [20].

Back propagation techniques have the potential to train DCNN, with the weight update is solved using the following formula:

$$\Delta w_{ij}(t+1) = \Delta w_{ij}(t) + \eta \frac{ac}{aw_{ij}}$$

among them, η is learning rate, c is cost function, i & j are the input unit and Δw_{ij} is the weight update of the function.

After gathering features from transformed 2-D images, the DCNN technique is built using the MATLAB software to categorise the input signals. To train the classifiers, we use feature maps as training data. The total amount of dataset for analysis is 16384, with a cumulative dataset of 120 instances per fault and a learning rate of 0.0001. The sampling rate used is 8.192 kHz, with a total of 25 epochs. To distinguish the training sample from the test sample, 70% of our dataset is utilized for classification purpose and 30% for testing. Based on the results for the testing dataset, the research constructed a confusion matrix to analyse the correctness of our study and confirmed that the previously mentioned strategies are effective.

3.0 RESULTS AND DISCUSSION

According to the study, the prolonged use of centrifugal pumps in the manufacturing industry generates many faults that must be properly maintained for optimum pump performance. The cavitation defect and outer race bearing seal fault are considered in this research. They are differentiated to the good state pump. Figure 2a depicts the bearing in good shape, while Figure 2b depicts the defective bearing seal failure. For the experiment, the healthy bearing is replaced with a outer race bearing seal fault, which generates a lot of sound in the pump and decreases the pump's performance. Another type of hydraulic failure cavitation is reproduced by reducing the pressure on the suction part of the pump, which causes the air bubbles in the fluid to collapse. Figures 2c and 2d show the preliminary healthy state impeller and defective impeller after cavitation.

Figure 2a Healthy bearing

Figure 2b Outer race bearing seal failure

Figure 2c Normal impeller

Figure 2d Defective Impeller

The sensor installed in the centrifugal pump is linked to the data collecting device for getting the pump's factors based on vibrational examination. The generated defects in the monoblock centrifugal pump produce time domain signals. The time domain signals relevant to a healthy pump are also captured and analyzed eventually. The amplitude vs sample length raw signal for the defect pump and healthy pump is displayed. The cavitation fault raw signal is shown in Figure 3a, the defect outer race bearing seal raw signal in Figure 3b, and the effective pump raw signal is depicted in Figure 3c. respectively. At every 15 mins from pressure 0.1 Kg/cm2 to 1.5 Kg/cm^2 the vibrational dataset readings are taken.

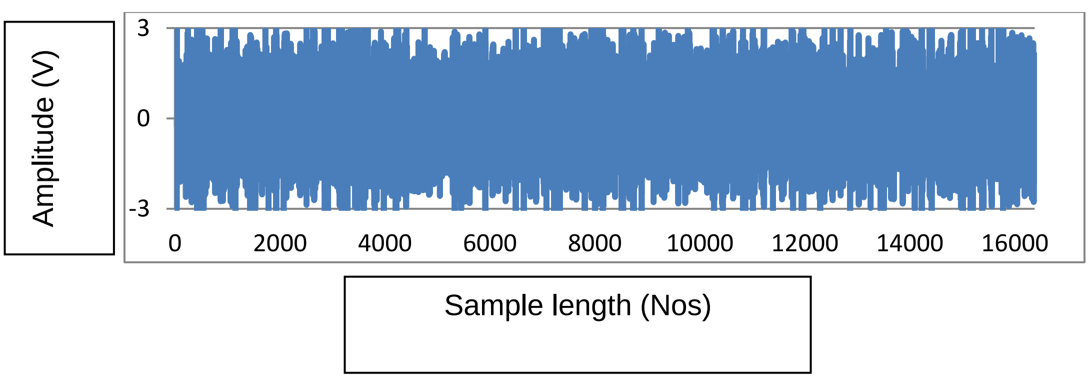


Figure 3a Cavitation raw signal

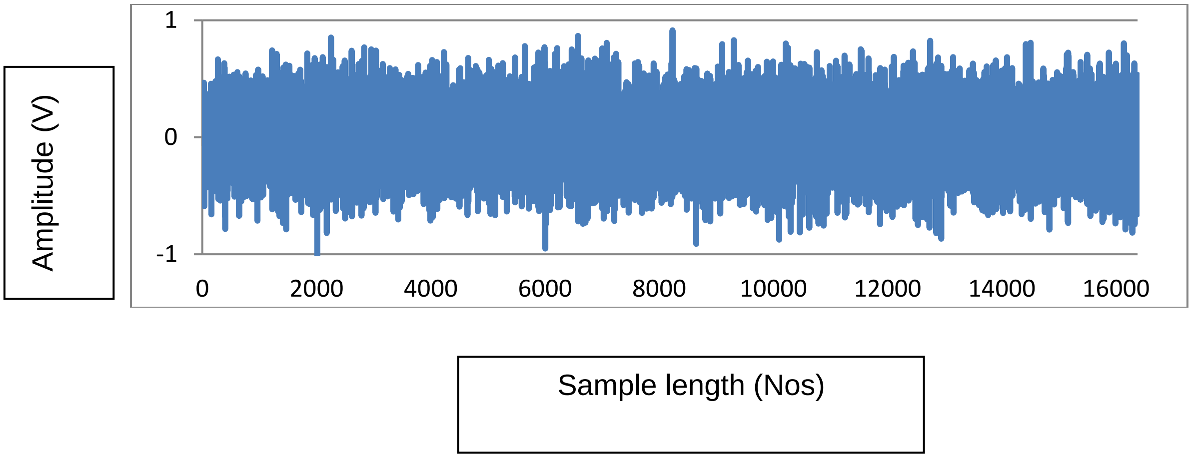


Figure 3b Outer race bearing seal raw signal

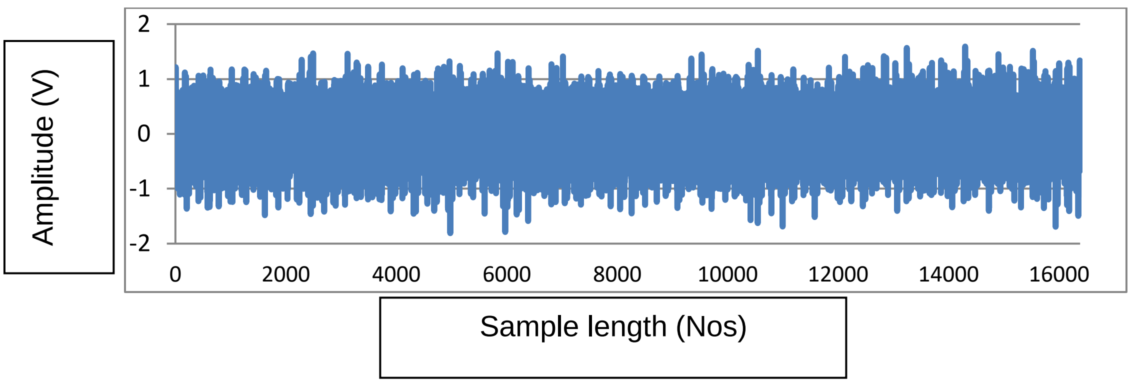


Figure 3c Healthy pump raw signal

Image Normalization

During this normalization approach by using energy values the vibration signals in the time range are changed into 2-D dimensions. Received signals are then intially segmented into equal subareas, that are each expressed as a frame. The frame length and harmonic frequency of a signal are multiplied to get the quantity of a frame. By partitioning the signal, the researchers were able to get a certain number of frames that are paired with fixture size, helped to determine the breadth and depth of the matrices. The fixture size is comparable to the length of the matrix, while the fixture quantity is equivalent to the matrix's width. For instance, if the fixture dimension is M and the fixture volume is N, the optimum dimension is MxN. The specified fixture energy levels then are joined into the matrix's cells. The value of each fixture is entered vertically into the matrix. The initial fixture optimum values are let into the matrix's initial column, with the first value going into the initial cell of the first row. The second value moves further into the initial unit of the next row. As a result, the first frame's result would be stored in the initial cell of the last column, and every result will fit into the column because the matrix's length equals the fixture size. One by one, the further fixture activity levels are entered into the matrix. Since the breadth of the matrix corresponds to the number of frames, the majority of the images may fit within it, and the data of the images are now standardized in the band of 0-120 after all the data have been put into the matrix. The matrix seems to have a lowest quantitative value of 0 and a maximum reference level of 120. All numerical values are derived within this range depending on the ratio. Inside the matrix, the true results replace the existing values. The normalization procedure helps to reduce the resolution of the original signal. This also helps to reduce disturbance in the signals received. Signal attributes in the time domain are kept in a 2-D representation, and texturing characteristics of the data in 2-D can be restored to classify the information. This analysis also make use of the frequency components which depicts the signal as a fusion of amplitude and phase values for each component frequencies. The signal are then converted to 2-D by using frequency domain.1) Every vibration signal is converted into frequency domain using the Fourier Transform. The intensities of the signal were then standardized to a range of 0-120. Figure 4a, b, c displays a 2D grey scale image of a healthy pump with three samples, while Figure 4d, e, f shows a grey scale image of a cavitation flaw in a pump with three samples.2) Figure 4g, h, i shows a greyscale image of a pump outer race bearing failure with three samples. Three ways are used to evaluate the image's rectification efficiency.

1) To calculate the overall average variance to obtain the reliability of the image. After performing image corrections, calculate the standard error and mean to calculate the median precision for each section. The estimate of each line's accuracy is the picture's comparative reliability. The following is the formula:

$$\varepsilon_{\mathrm{i}} = \frac{1}{CN_i}\sqrt{\frac{1}{N}\Sigma_{j=1}^{n}[CN(i,j) - \overline{CN_j}]2}$$

$$\varepsilon = \frac{1}{\mathrm{m}}\Sigma_{i=1}^{m}\varepsilon_i$$

Among these, $\varepsilon_i$is the image's relative scaling accuracy for the i-th line, and CNi is the image's average value for the i-th row.

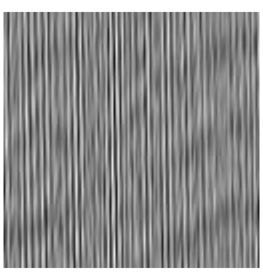
Average line standard deviation method. Calculate the corresponding standard deviation after calculating the average values of each column after image processing. The relative accuracy of the image is calculated by dividing the image average value. The following is the formula for calculating the relative accuracy:

$$\varepsilon = \frac{1}{\mathrm{CN}}\sqrt{\frac{1}{N}\Sigma_{j=1}^{n}[CN(j) - \overline{CN}]^2}$$

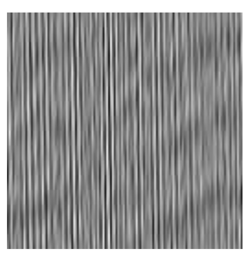
CN(i,j) is the CN of the j-th column of the i-th row of the image, where the number of probes is n and the image size is mxn.

3) Generalized noise method. Unlike the other two techniques, the generalised noise method determines the average value of each column after image corrections, as well as the image mean value. The absolute value is obtained first, then second the estimated value, and finally the percentage of the normalised value of the complete image. The formula for calculating the average value is as follows:

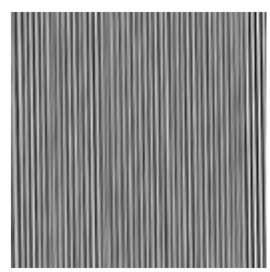
$$\varepsilon = \frac{1}{\mathrm{CN}}\frac{1}{N}\Sigma_{j=1}^{n}[CN(j) - \overline{CN}]$$



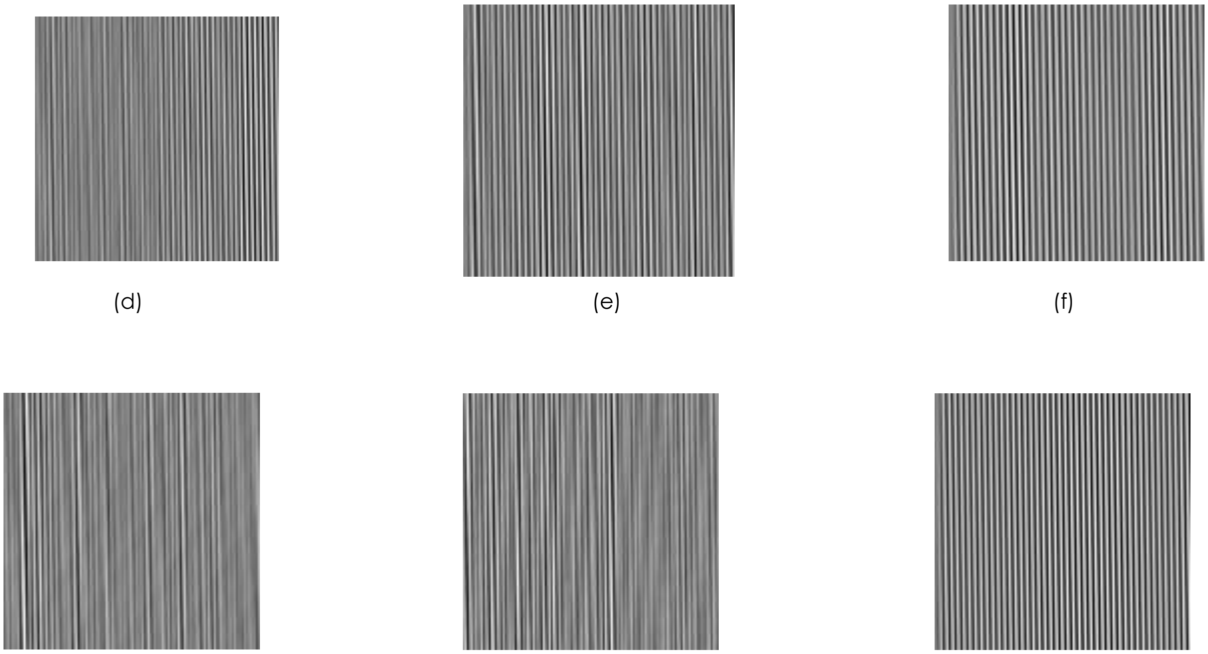
(a)



(b)



(c)



(d) (e) (f)

(g) (h) (i)

Figure 4 Grey level image for healthy pump, cavitation defect & bearing defect failure

Defect Categorization Using Deep Learning Algorithm

To improve the process, the created system is put though the deep convolutional neural network layers. The DCNN is made up of several layers that work together to process the input layer (convolutional layers, fully linked layers, pooling layers, activation function, and severalfeasible output layers) as shown in Figure 5. The DCNN variables that were are evaluated are listed in Table 1. The fault accuracy of the centrifugal pump is examined for the method developed by CNN's multiple computational levels. From the whole dataset of 16384 instances, the training set has 11468 instances and the test dataset includes 4916 instances.The overall samples are analyzed in the system by a sampling rate of 8.192 kHz. The training data consideration is about of 70% and the testing data consideration of 30%.The main primary component of CNN is the convolution layer. The layer has many kernels present in the image. During the training process the numbers of kernels present in the image are learnt. The beginning layers are designed for extracting the general features, and as the network becomes deeper, the complex components are eliminated.

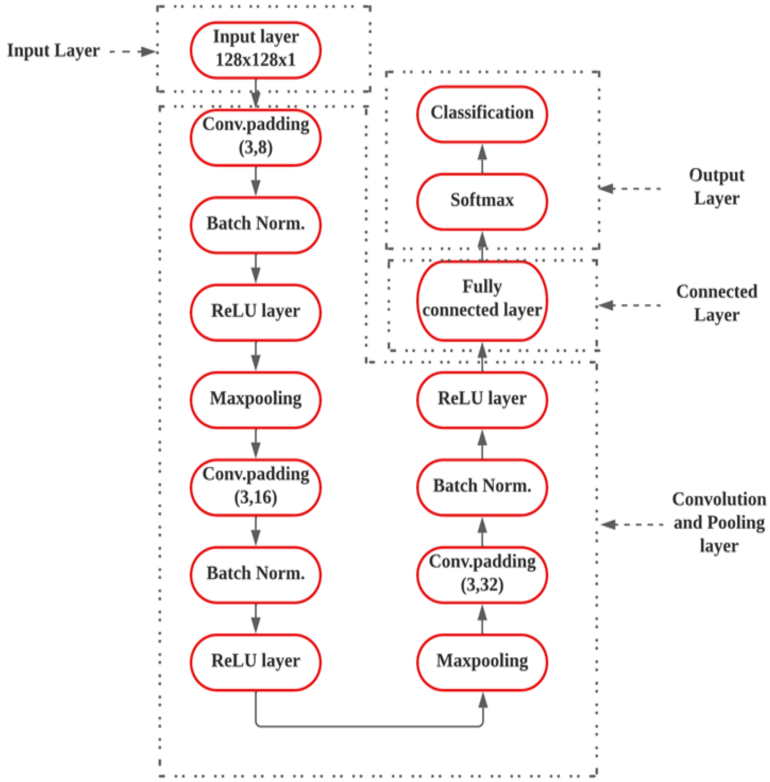


Figure 5 DCNN architecture

Table 1 Description of DCNN parameters

S.No	Description	Value
1	No.of Convolution	3
2	Kernel pixel	(256, 512)
3	Size of kernel	(5x1,5x1)
4	Max pooling layers	2
5	Size of pooling layer	(3x1,3x1)
6	Activation function	ReLU
7	Learning rate	0.0001
8	Max Simulations	75
9	Mini group size	32
10	Iteration considered	25
11	Simulation per epoch	3

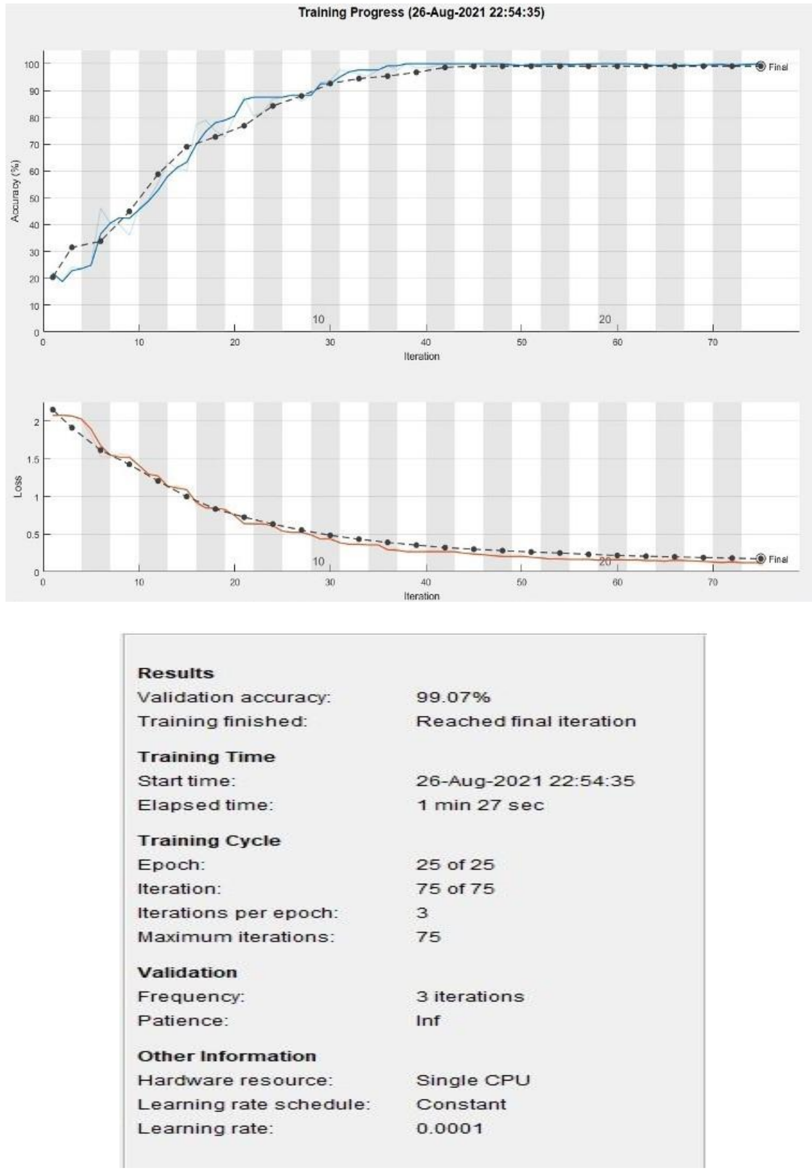


Figure 6 Training data validation

The features are filtered for data validation using the DCNN classifier, and the testing data set is also extracted for feature selection using the classifier, and the dataset are classified. Figure 6 shows the training data validation for the two faults and a healthy good pump considered. The overall validation precision of the present system is analyzed as 99.07 % for the testing and training, the processing time for the CNN classifier is 1 min 27 seconds, having the epochs of 25 with three iterations per epoch at the learning rate of 0.0001.

The predicted class accuracy and true class accuracy for the classified fault conditions are shown in the Table 2. The fault conditions are analyzed with the good pump compared with the fault conditions are Cavitation fault and outer race bearing seal failure. The Prediction class accuracy for the GP, CF and BS classes is 97.3%, 100% and 100%. Similarly, the CNN classifier's true class accuracy for the GP, CF and BS are 100%, 100% and 97.2%. Finally, the overall accuracy of the proposed system with DCNN architecture is calculated as 99.07%.

Table 2 Predicted class accuracy and true class accuracy

Fault condition	Predicted class accuracy	True class accuracy
Healthy Pump	97.3%	100 %
Cavitation	100%	100 %
Outer race bearing seal fault	100 %	97.2%

Comparison with ML Algorithm

The vibrational features obtained from the good pump and other faulty conditions are taken for statistical analysis using the Waikato Environment for Knowledge Analysis software. From the received vibration features 50 samples are taken for comparison with ML algorithms. In this research the features are classified through random forest to find the fault accuracy. To facilitate the feature extraction process, the mean, median, mode, minimum, maximum, range, skewness etc., are computed and few sample readings are shown in Figure 7.

Feature Extraction - Statistical analysis												
Mean	Standard error	Median	Mode	Standard	Sample variance	Kurtosis	Skewness	Range	Minimum	Maximum	Sum	Condition
4.84E-06	6.00E-06	1.46E-06	-4.37E-05	6E-04	3.69E-07	7.33820	-0.855	0.01	0.008	0.002	0.0495	Good pump
1.54E-05	6.42E-06	2.91E-05	-4.56E-05	6E-05	4.22E-07	3.57474	-0.3667	0.009	-0.01	0.002	0.1579	Good pump
8.55E-06	6.88E-06	2.91E-05	9.72E-05	7E-04	4.84E-07	7.12749	-1.0033	0.011	-0.08	0.003	0.0876	Good pump
6.42E-05	3.82E-06	8.26E-05	4.37E-05	4E-04	1.46E-07	10.2128	-1.4318	0.006	-0.04	0.001	0.6423	Cavitation
4.15E-05	3.94E-06	5.34E-05	4.28E-05	4E-04	1.55E-07	64.1741	-4.3855	0.01	-0.08	0.002	0.4154	Cavitation
5.50E-05	4.19E-06	7.72E-05	4.28E-05	4E-04	1.75E-07	144.706	-7.1588	0.013	-0.07	0.002	0.5956	Cavitation
2.12E-05	4.14E-06	2.43E-05	4.87E-05	4E-04	1.47E-07	8.21249	-0.8574	0.009	-0.04	0.004	0.7546	Bearing seal fault
4.15E-05	3.94E-06	5.34E-05	4.28E-05	4E-04	1.62E-07	6.17524	-3.5657	0.007	-0.08	0.002	0.5354	Bearing seal fault
5.50E-05	4.19E-06	7.72E-05	4.28E-05	4E-04	1.75E-07	8.52479	-4.7541	0.006	-0.05	0.002	0.8463	Bearing seal fault

Figure 7 Feature extraction

After completing the statistical feature extraction, the variables are generated to categorize the features. The statistical element is utilized during the selection of features. descriptive statistical features were computed using Microsoft Excel. After opening a raw signal, the appropriate statistical tool from the data processing device pack are utilized to calculate the statistical parameters of the signal. The above procedure must be repeated for each of the files, so a macro coding is created in order to achieve the data. The end product will be a unique file stored in .CSV (comma separated value) that ML classifiers could use as input for training process.

Classification using Random Forest

In the Waikato Environment for Knowledge Analysis (Weka) there are various variety of classifiers using ML algorithms such as trees, bayes, functions, meta etc., Initially, the training is performed using a tree-based approach. In the tree type RF technique is utilized to find the accuracy of correctly classified instances. From the study 70 % of the data are used for training. Total data set taken for study is 150 with 50 samples per fault for training using the algorithm. The confusion matrix is shown in Table 3. From the Table 3 the main inference for good pump is that they don't have any misclassification whereas for cavitation fault and outer race bearing fault there is misclassification identified.

Table 3 Confusion matrix using random forest

Good Pump	Cavitation	Outer race bearing seal	Classification
50	0	0	Good Pump
9	41	0	Cavitaion
8	0	42	Outer race bearing seal

From the statistical analysis the stratified cross validation with respect to random forest algorithm is shown in Table 4. The correctly classified instances is high at 96.51% for random forest Ml algorithm and the proposed DCNN algorithm shows an accuracy of 99.07% respectively as shown in Table 5.

Table 4 Cross validation using random forest

Features	Random Forest
Correctly Classified Instances	96.51%
Incorrectly Classified Instances	3.29%
Kappa coefficient	0.96
Mean absolute error	0.031
RMS error	0.0954
Relative absolute error	10.95%
Root relative squared error	27.76%
Total Number of Instances	150 Nos

Table 5 Comparison with proposed DCNN algorithm

S.No	Algorithm	Individual fault accuracy
1	Random Forest	96.71 %
2	Proposed Deep Convolutional Neural Network	99.07 %

4.0 CONCLUSION

For fault detection, neural network algorithms are employed in a variety of industrial applications such as turbines, pumps, and hydraulic equipment. For quicker solutions and optimum accuracy, experiment analyzes for industrial monoblock centrifugal pump defect diagnosis are performed. The suggested method integrates vibration signals with grey level pictures based on normalisation, with the outcomes acquired at high resolution for great accuracy. The given DCNN system categorises grey imaging using its convolution, pooling, and fully connected layers, with ReLU serving as the activation layer. For more precise findings, time domain vibrational signals relevant to good pump, outer race bearing seal failure, and cavitation fault are identified and trained. From the confusion matrix the true class accuracy and the predicted class accuracy for the faults in the monoblock centrifugal pump are calculated. From the fault diagnosis based on the DCNN classifier for the pump the overall efficiency is found to be 99.07% after training. With the same dataset using Random forest algorithm the individual fault accuracy is 96.71 %. The proposed DCNN algorithm is found to be the highest when compared with the random forest algorithms. In the future work the other faults in the centrifugal pump can be analyzed by using the same DCNN classifier for better results.

Future Scope

The suggested method of fault analysis can be extended with other faults, such as motor fault, fitting fault, seal fault etc. In the industrial pump, faults can occur for many reasons that may prevent the plant from properly functioning. The causes of the multiple faults need to be examined, and the same methodology must be carried out to determine the accuracy of the predictive fault diagnosis.

Conflicts of Interest

The author(s) declare(s) that there is no conflict of interest regarding the publication of this paper.

Acknowledgement

This research is fully supported by Department of Mechanical Engineering, SRM Institute of Science & Technology, Kattankulathur.

References

[1] Azadeh, A., Saberi, M., Kazem, A., Ebrahimipour, V., Nourmohammadzadeh, A. and 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. https://doi.org/10.1016/j.asoc.2012.06.020.

[2] Muralidharan V., Sugumaran, V. and Indira, V. 2014. Fault Diagnosis of Monoblock Centrifugal Pump using SVM. *Engineering Science and Technology, an International Journal*. 17(3): 152-157. https://doi.org/10.1016/j.jestch.2014.04.005.

[3] Muralidharan, V. and Sugumaran, V. 2013. Feature Extraction using Wavelets and Classification through Decision Tree Algorithm for Fault Diagnosis of Mono-block Centrifugal Pump. *Measurement.* 46(1): 353-359. https://doi.org/10.1016/j.measurement.2012.07.007.

[4] Gao, Z., Cecati, C. and Ding, S. X. 2015. A Survey of Fault Diagnosis and Fault-tolerant Techniques—Part I: Fault Diagnosis with Model-based and Signal-based Approaches. *IEEE Transactions on Industrial Electronics.* 62(6): 3757-3767. https://doi.org/10.1109/TIE.2015.2417501.

[5] Tian, Y., Lu, C. and Wang, Z. L. 2015. Approach for Hydraulic Pump Fault Diagnosis based on wpt-svd and svm. *Applied Mechanics and Materials*. 764: 191-197. https://doi.org/10.4028/www.scientific.net/AMM.764-765.191.

[6] Jiang, W., Li, Z., Zhang, S., Wang, T. and Zhang, S. 2021. Hydraulic Pump Fault Diagnosis Method Based on EWT Decomposition Denoising and Deep Learning on Cloud Platform. *Shock and Vibration.* https://doi.org/10.1155/2021/6674351.

[7] Bin, G. F., Gao, J. J., Li, X. J. and Dhillon, B. S. 2012. Early Fault Diagnosis of Rotating Machinery based on Wavelet Packets—Empirical Mode Decomposition Feature Extraction and Neural Network. *Mechanical Systems and Signal Processing.* 27: 696-711. https://doi.org/10.1016/j.ymssp.2011.08.002.

[8] Tang, S., Yuan, S. and Zhu, Y. 2019. Deep Learning-based Intelligent Fault Diagnosis Methods Toward Rotating Machinery. *IEEE Access.* 8: 9335-9346. https://doi.org 10.1109/ACCESS.2019.2963092.

[9] LeCun, Y., Bengio, Y. and Hinton, G. 2015. Deep Learning. *Nature.* 521(7553): 436-444. https://doi.org/10.1038/nature14539.

[10] Lu, C., Wang, Z. Y., Qin, W. L. and Ma, J. 2017. Fault Diagnosis of Rotary Machinery Components using a Stacked Denoising Auto Encoder-Based Health State Identification. *Signal Processing.* 130: 377-388. https://doi.org/10.1016/j.sigpro.2016.07.028.

[11] G. E. Hinton, and R. S. Ruslan. 2006. Reducing the Dimensionality of Data with Neural Networks. *Science.* 313(5786): 504-507. https:// DOI: 10.1126/science.1127647.

[12] Liu, R., Yang, B., Zio, E. 2018. Artificial Intelligence for Fault Diagnosis of Rotating Machinery: A Review. *MechSyst Sign Process.* 108: 33-47. https://doi.org/10.1016/j.ymssp.2018.02.016.

[13] Li, J., Wang, H., Wang, X. 2020. Rolling Bearing Fault Diagnosis based on Improved Adaptive Parameterless. *Empirical Wavelet Transform and Sparse Denoising Measurement.* 152: 107392. https:10.1016/j.measurement.2019.107392.

[14] Manikandan, S. and Duraivelu, K. 2021. Fault Diagnosis of Various Rotating Equipment using Machine Learning Approaches–A Review. *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering.* 235(2): 629-642. https://doi.org/10.1177/0954408920971976.

[15] 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. *J. Vib. Eng. Technol*. 11: 141-152. https://doi.org /10.1007/s42417-022-00566-0.

[16] Guo, X., Chen, L., Shen, C. 2016. Hierarchical Adaptive Deep Convolution Neural Network and Its Application to Bearing Fault Diagnosis. *Measurement*. 93: 490-502. https://10.1016/j.measurement.2016.07.054.

[17] A. L. Dias, J. T. da Silva, A. C. Turcato and G. S. Sestito. 2021. An Intelligent Fault Diagnosis for Centrifugal Pumps based on Electric Current Information Available in Industrial Communication Networks. *14th IEEE International Conference on Industry Applications (INDUSCON)*. 102-109. https://10.1109/INDUSCON51756.2021.9529678.

[18] Osmana, A., Salman, A., Fawzy, K. 2019. Vibration Signature of Misaligned Rotors of Centrifugal Pump. *Egyptian Journal for Engineering Sciences and Technology.* 27: 30-42. https://10.21608/eijest.2019.97279.

[19] Jia, F., Lei, Y., Lin, J., Zhou, X., Lu, N. 2016. Deep Neural Networks: A Promising Tool for Fault Characteristic Mining and Intelligent Diagnosis of Rotating Machinery with Massive Data. *Mechanical Systems Signal Processing*. 72-73: 303-315. https://doi.org/10.1016/j.ymssp.2015.10.025.

[20] Tiboni, Monica and Remino, Carlo and Bussola, Roberto and Amici, Cinzia. 2022. A Review on Vibration-Based Condition Monitoring of Rotating Machinery. *Applied Sciences.* 12: 03. https://doi.org/10.3390/app12030972.