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A Comparative Study between Support Vector Machine (SVM) and Extreme Learning Machine (ELM) for Fault Detection in Pumps

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Abstract

Background/Objectives: To apply Support Vector Machine and Extreme Learning Machine for fault diagnosis of centrifugal pump and to compare them with respect to classification accuracy and learning time. The overall best one is reported. **Methods/Statistical Analysis**: The vibration signals are extracted from the experimental setup. Then signals are then filtered and trimmed for ease of processing. The wavelet features are extracted in its discrete form thus it forms the feature set. The set of features are then fed as an input and classified using Extreme Learning Machine and Support Vector Machine. These two algorithms are state of the art techniques for classification of different conditions of the setup. The results are compared with respect to classification accuracy and learning rate. Finally, it is concluded that the ELM could achieve 99.2% classification accuracy at a very faster rate than SVM. **Application/Improvements:** Extreme Learning Machine has been used for the first time for fault diagnosis applications. Discrete wavelet transform features in combination with ELM have been attempted for the first time. To conclude, ELM could act as a better alternate for machine learning approach.

Keywords: Extreme Learning Machine, Fault Diagnosis, Pump,Support Vector Machine

1. Introduction

Continuous monitoring of the pump has been essential to reduce the breakdowns in order to increase the productivity. The pumps are the central part in food industry, waste water treatment plants, agriculture, oil & gas industry, paper & pulp industry, etc. In a monoblock centrifugal pump, bearing and impeller are the integral components that have a very high influence on the pump characteristics. In a monoblock centrifugal pump, defective bearing, defect on the impeller and cavitation occur which lead to a very serious problems such as heavy noise, leakage, high vibration, etc. Cavitation can cause more undesirable effects, such as deterioration of the hydraulic performance (drop in head capacity and efficiency), damage of the pump by pitting, erosion and structural vibration. Vibration signals were widely used in condition monitoring of centrifugal pumps. Fault detection was achieved by comparing the signals of monoblock centrifugal pump running under normal and faulty conditions. The faults considered in this study were BF, IF, BFIF and CAV. By the application of piezoelectric transducers, the vibration levels were measured for each condition. The level of vibration could be compared with historical baseline value to assess the severity. Understanding the vibration signal and interpreting them according to the desired application demands the strong knowledge in the relevant field and rich domain expertise. Usual methodology adopted to accomplish this task was to extract the energy level present in the signal. This energy level corresponds to certain mechanical component or certain malfunction. The drawback with the traditional techniques such as Fast Fourier Transforms, Fourier Transforms was that the signal could either be represented in time domain or in

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frequency domain. However, the monoblock centrifugal pump being a rotating component produces highly non stationary signals in which the characteristic frequency may change with respect to time. Hence, the signal should have both time and frequency representation. Though there were several methodologies to extract the energy content in the signal, wavelets in its discrete form has been chosen for the present study. The features have been extracted using DWT as it represents the original signal in both time frequency domain. Another challenge was to choose the right classifier to perform the classification process and validation. There were lots of algorithms suggested by the researchers for their amazing performance such as ANN, SVM and decision tree algorithms. Still, these algorithms have the drawback of slow training for huge datasets. Hence, in the present study Extreme Learning Machine (ELM) has been taken for the study as it overcomes the drawbacks of the above algorithms.

2. Related Work

"J.J. Jeng and C. Y. Wei proposed an online condition monitoring and diagnostic system for feed rolls. This system measures the bearing vibration signals and judges the feed roll condition automatically according to the diagnostic rules stored in a computer[1]. C.F.Yan and H. Zhang presented a novel real-time fault diagnostic system for steam turbine generator set by using strata hierarchical artificial neural network, where a set of faults were created and the corresponding signals stored in a computer to extract the features. The derived features then used for classification using artificial neural network. The results show a promising performance[2]. H.R. DePold and F.D.Gass performed a similar exercise on the gas turbine prognostics and proved the worth of knowledge structure extracted using expert system[3]. X. Wang and S. Z. Yang presented a parallel distribution methodology for fault diagnosis of turbine generator. In this paper, major faults were introduced one at a time and the respective signals acquired for that condition. Finally, the classification was done using parallel distribution technique and proved that the methodology was fit for that application[4,5]. V.Sugumaran et.al., proposed a new technique of feature extraction using statistical methods and feature selection using decision tree algorithms for fault diagnosis of roller bearing. A set of statistical features such as mean, median, mode, skewness, kurtosis, maximum value, minimum value, sum were extracted from the vibration signals. From this, only few dominant features have been selected using decision tree algorithm for feature classification using SVM and PSVM. The result shows it suits very much for the rotating components[6]. Huang G. B., & Siew, C. K. used extreme learning machine (ELM) with randomly assigned RBF kernels for fault diagnosis applications[7]. Jiang L, Liu Y, Li X, Tang S used bisectral distribution as feature for classification of faults in rotating machineries[8] whereas orthogonal distribution approach was performed by[9,10].

Lhermitte S, Verbesselt J, Verstraeten WW, Coppin P compared the time series similarity measures for classification of dynamic systems where the signals were acquired in time domain and comparison has been made with respect to classification[11] Liu L, McLernon D, Ghogho M, Hu W, Huang J detected the ballistic missile via micro-Doppler frequency estimation from radar return in which radar signals were employed for the detection process using MATLAB toolbox[12,13]. Wavelets have been effectively used in variety of applications Nejad FM, Zakeri H. attempted with pavement distress classification with wavelet transform and ANN. In this paper, wavelet in its discrete form was used to extract the features and ANN was used for classification[14]. Nelson DE, Starzyk JA, Ensley DD tried with iterated wavelet transforms as features using radar signals in HRR target recognition. Where, the radar signals were used to extract the feature set to represent the knowledge structure[15]. Tabib M. V et.al, proposed that the wavelet transforms could be effectively used in flow structures as well in time domain[16] whereas Tang X attempted with wavelet transforms for geological disaster prediction[17]. Wang Y et.al. made a detailed study on effectiveness of extreme learning machine for fault diagnosis application[18] and Wink attempted with polyphase decomposition and discrete wavelet transforms in frequency domain[19]. Muralidharan V, Sugumaran V presented a study on fault diagnosis of monoblock centrifugal pump with wavelet features and decision tree based classification[20], roughest for rule generation and fuzzy engine for classification[21] , wavelet decomposition using discrete wavelets and SVM for classification of faults[22] and wavelet features with SVM[23]. In all these methods, the results were encouraging. However, in all of the above algorithms the learning speed was relatively low which lead to delayed diagnosis of the conditions of the pump. Moreover, large amount of literature exists for the classification of faults in centrifugal pump, but fault diagnosis using ELM in combination with wavelets were not reported which forms the basis for this study. Hence, the ELM algorithm was chosen to make classifier learn at faster rate without losing classification performance and to compare the results with that of SVM."

The rest of the paper is organized as follows: section 3 deals with the experimental setup and data acquisition. Section 4 details the concept of DWT and feature extraction. The concept of ELM and SVM is presented in section 5 and section 6 summarizes the result and in section 7 conclusions are presented.

3. Experimental Studies

The principle thought of the review was to distinguish whether the monoblock radial pump in great condition or in broken condition at a generally quicker rate by utilizing ELM and to contrast the outcomes and SVM. The monoblock radial pump with sensor and information obtaining is talked about in the accompanying points under development of the model and method separately.

3.1 Construction

The monoblock centrifugal pump for condition monitoring was taken for this study. The motor (2 hp) was used to drive the pump. The flow at the inlet and the outlet of the pump can be adjusted by the valve control system. By adjusting the inlet valve, pressure drop was created between the suction head and the eye of an impeller that simulates cavitation. It can be realized with the help of an acrylic pipe of one meter length fitted on the inlet and at the outlet of the impeller. Piezo-electric type accelerometer was used to measure the vibration signals. The accelerometer was mounted on the pump inlet using adhesive. The accelerometer was connected to the signal conditioning unit where the signal goes through the charge amplifier and an Analog to Digital Converter (ADC) and stored in the memory. Then the signal was processed from the memory to extract the wavelet features. The schematic diagram of fault diagnosis of monoblock centrifugal pump set up is shown in Figure1.

The sampling frequency of 24 kHz and sample length of 1024 were considered for all conditions of the pump. The sample length was chosen arbitrarily to an extent; however, the following points were considered. After calculating the wavelet transforms it would be more meaningful when the number of samples was more. On the other hand, as the number of samples increases, the computation time increases. To strike a balance, sample length of around 1000 was chosen. The nearest 2^n to 1000 is 1024; hence it was taken as sample length. 250 trials were taken for each monoblock centrifugal pump condition, and vibration signals were stored in the data files. Figure 2 shows the time domain signals taken from monoblock centrifugal pump for 5 different conditions. They show time domain plots of vibration acceleration of pump under normal condition (GOOD) (without any fault), pump with bearing fault (BF), pump with impeller fault (IF), pump with both bearing and impeller fault (BFIF), and cavitation (CAV) respectively. Referring to Figure 2, one can understand that the sample number was taken along the abscissa and the amplitude along the ordinate. Thus understanding the pattern followed by each condition of the pump will be clear.

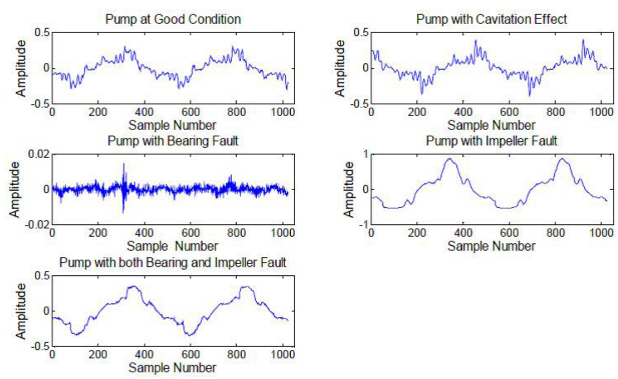

Figure 2. Vibration pattern for the faults.

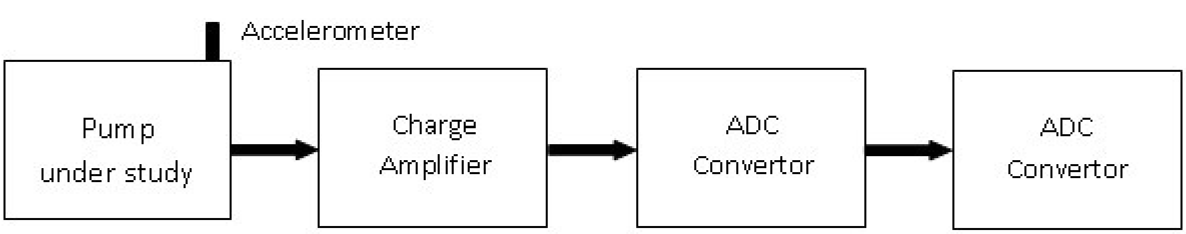

Figure 1. Schematic diagramof monoblock centrifugal pump.

4. Feature Extraction using DWT

The time domain signal can be used to perform fault diagnosis by analyzing vibration signals obtained from the experiment. "Discrete wavelet transform (DWT) has been broadly utilized and gives the physical qualities of time-recurrence space information. Wavelet investigation of vibration signs yields distinctive engaging parameters. Decently, a wide arrangement of parameters were chosen as the reason for the review. These elements were separated from vibration signals. In this paper, DWT of various variants of various wavelet families have been considered. The rundown of families considered for this review is given beneath:

1. Daubechies wavelet (db1, db2, db3, db4, db5, db6, db7, db8, db9, db10)
2. Coiflet (coif1, coif2, coif3, coif4, coif5)
3. Biorthogonal wavelet (bior1.1, bior1.3, bior1.5, bior2.2, bior2.4, bior2.6, bior2.8,
bior3.5, bior3.7, bior3.9, bior4.4, bior5.5, bior6.8)
4. Reversed biorthogonal wavelet (rbio1.1, rbio1.3, rbio1.5, rbio2.2, rbio2.4, rbio2.6,
rbio2.8, rbio3.1, rbio3.3, rbio3.5, rbio3.7, rbio3.9, rbio4.4, rbio5.5, rbio6.8)
5. Symlets (sym2, sym3, sym4, sym5, sym6, sym7, sym8)
6. Meyer wavelet.

A careful perusal of the signal details under different conditions brings out that there are considerable changes in the average energy level of the signal details with respect to its conditions. Feature extraction constitutes computation of specific measures, which characterize the signal. The DWT provides an effective method for generating features. The collection of all such features forms the feature vector. A feature vector is given by

$$v^{dwt} = \{v_1^{dwt}, v_2^{dwt} \dots v_8^{dwt}\}^T \qquad (1)$$

A component in v_i^{dwt} the feature vector is related to the individual resolutions by the following equation

$$v_i^{dwt} = \frac{1}{n_i}\sum_{j=1}^{n_i} w_{i,j}^2 \quad , i = 1, 2, 3 \dots 8 \qquad (2)$$

v_i^{dwt} the i^{th} feature element in a DWT feature vector. n_i is the number of samples in a $w_{i,j}^2$ individual sub-band, is the j^{th} detail coefficient (high frequency component) of the i^{th} sub-band. The wavelets considered for the present investigation are Haar (db1), Daubechies, symlets, Coiflets, biorthogonal, reverse biorthogonal and Meyer (dmey). All the wavelets are considered in the DWT form. The '*db5*' decomposed detail coefficient plots of different conditions of the pump have been presented up to 8 levels in Figure3 to Figure 8.

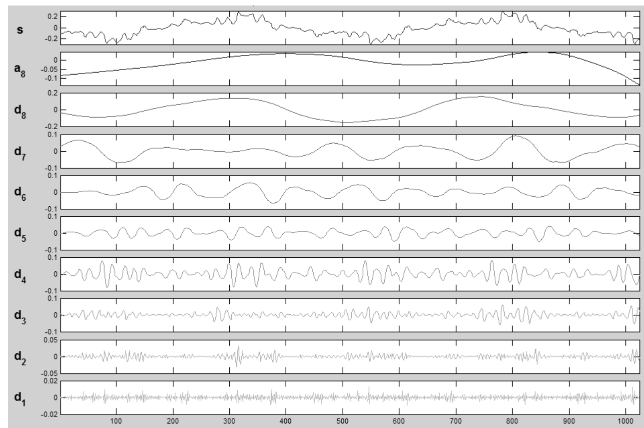

Figure 3. 'db5' decomposed detail plot for pump at good condition.

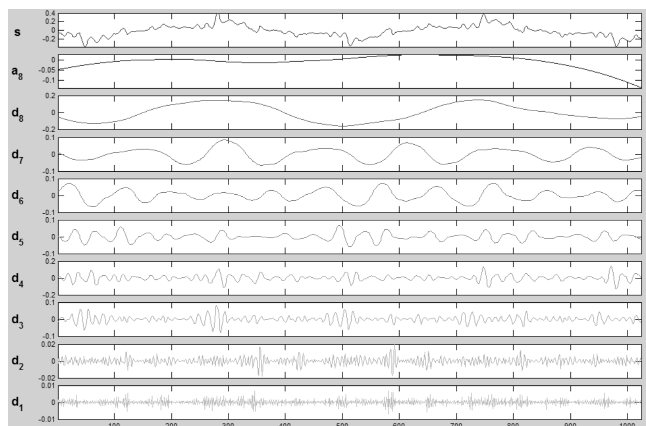

Figure 4. 'db5' decomposed detail plot for pump with bearing fault condition.

5. Classifiers

5.1 Extreme Learning Machine

ELM is one of the compelling learning calculations of Self Learning Forward Network (SLFN). It can be utilized

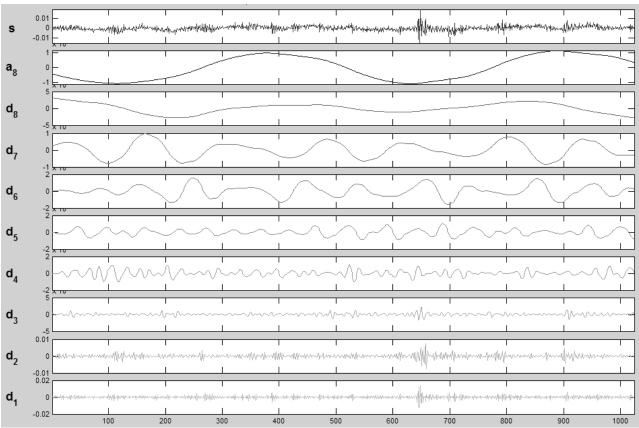

Figure 5. 'db5' decomposed detail plot for pump with impeller fault condition.

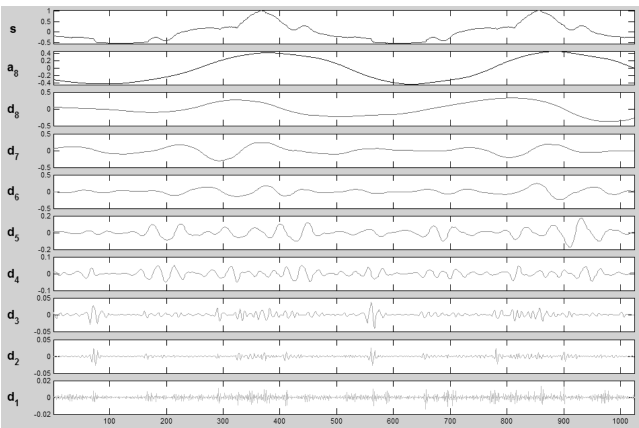

Figure 6. 'db5' decomposed detail plot for pump with impeller fault condition.

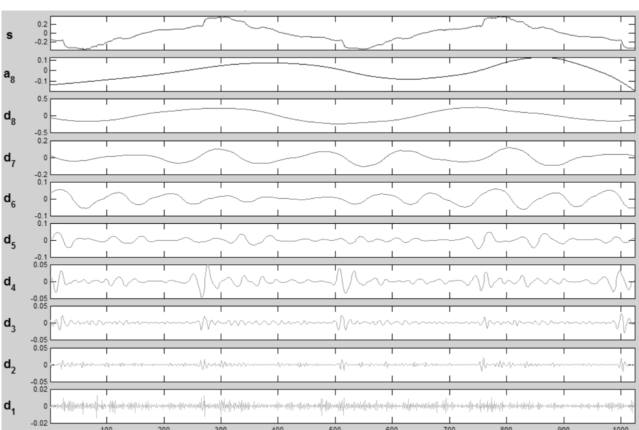

Figure 7. 'db5' decomposed detail plot for pump with impeller fault condition.

to tackle the issue which the customary innovation can't work. In the current neural system structures, SLFN is a standout amongst the most ordinarily utilized structures. It has been demonstrated that if the initiation capacity

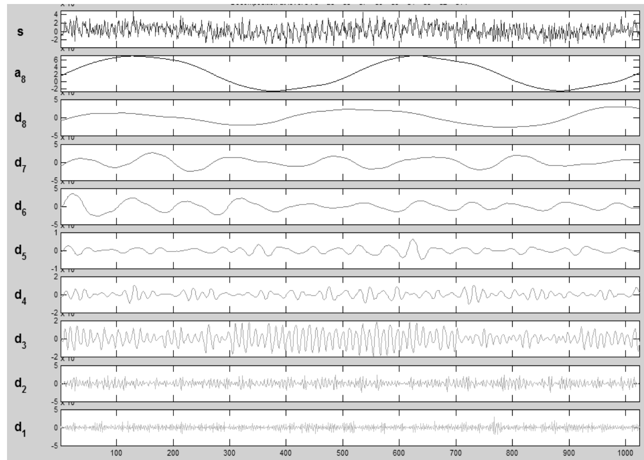

Figure 8. 'db5' decomposed detail plot for pump with impeller fault condition.

is chosen legitimately, SLFN can rough any capacity by a subjectively little mistake. ELM's info weights and the concealed layer edge qualities are chosen haphazardly, so the yield lattice of the shrouded layer is known. At that point its yield weights can be gotten from the summed up backwards framework. In a great deal of reasonable applications, the calculation has been demonstrated that it can accomplish great outcomes with quick learning speed. It has N hidden nodes, n input nodes, m output nodes. For M independent samples (x_i,t_i), where $x_i \in R^n$, $t_i \in R^m$ standard SLFN with N hidden nodes and activation function $g(x)$ can be modeled as

$$\sum_{i=1}^{N}\beta_i g(x_j) = \sum_{i=1}^{N}\beta_i g(w_i \,.\, x_j + b_i) = o_j \;, j = 1 \;....\; m \quad (3)$$

Where $w_i = [w_{i1}, w_{i2} \dots w_{in}]^T$ is the weight vector connecting the ith hidden node with the input nodes, $\beta_i = [\beta_{i1}, \beta_{i2} \dots \beta_{im}]^T$ is the weight vector connecting the i^{th} hidden node with the output nodes, and b_i is the threshold of the i^{th} hidden node $w_i * x_i$ denotes the inner product of w_i and x_i. For a group of given input samples (x_i,t_i), $x_i \in R^n$, $t_i \in R^m$, activation function $g(x)$, and network structure including N hidden nods, ELM algorithm steps are as follows:

(1)Randomly generate the input weights w_i and the thresholds $b_i, i = 1,2, \dots N$;

(2) Calculate the hidden output matrix;

(3) Calculate the output weight value β, $\beta = H^T T$ where $T = [t_1 \dots t_M]^T$

When the number of samples is large, there exists a large amount of calculation in implementation of matrix multiplications of input weight matrix w_i which randomly generates and samples matrix x_i. Here in order to simplify the calculation of the network in our implementation, every time only one row of w_i is generated and multiplied with sample matrix. After i times calculation, one can attain $w_i * x_i$.

5.2 Concept of SVM

Data mining techniques are being increasingly used in many modern organisations to retrieve valuable knowledge structures from databases, including vibration data. An important knowledge structure that can result from data mining activities is SVM. Consider the problem of classifying m points in the n-dimensional real space R^n, represented by the $m \times n$ matrix A and $m \times m$ diagonal matrix D with plus ones or minus ones along its diagonal according to membership of each point O_i in the class A+ or A–. Refer Figure 9 for the graphical representation of the SVM classifier.

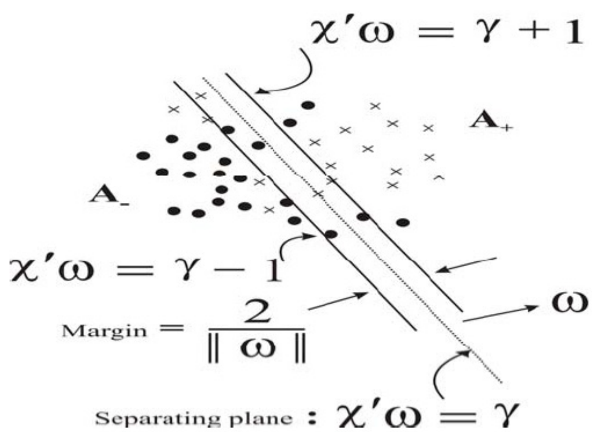

Figure 9. SVM formulation with soft margin (boundary).

6. Results and Discussion

The dataset has been classified with SVM algorithms and ELM algorithm (MATLAB implementation). The suitable orientation parameters and kernels have been chosen for the classification algorithms after trying with various values (For SVM nu =0.3 and for ELM, RBF kernel). Table 1 gives the learning speed and classification accuracies with SVM and ELM. From Table 1, one can derive the following observations.

(i) The table has been made with all mother wavelets and its versions.
(ii) The second column learning time (in sec) denotes the CPU time taken for the execution of the classification algorithm for the pump dataset. Similarly, the third column '% accuracy' denotes the classification accuracy. For example, the row 1 implies that the wavelet Bior1.1 could achieve a classification accuracy of 94.68 % in 0.81 sec with SVM and 99.68% in 0.47 sec with ELM.
(iii) From the table, one can understand that the CPU time taken for execution of the algorithm ELM has been comparatively less than that of SVM. Going further, SVM could give a maximum of accuracy of 98.84 in 0.25 secs whereas ELM could give 99.92 in 0.13 secs.
(iv) Though the difference between the classification accuracies has been almost negligible, the CPU time for the computation of the algorithm between SVM and ELM has been significant when the large dataset is considered for the study.

As discussed earlier, the main objective of this study in identifying the faster learning algorithm for fault diagnosis application, the ELM shall be suggested for faster learning of training dataset for the classification purpose.

The characterization consequences of best wavelet with ELM have been exhibited as a perplexity lattice. The disarray framework can be translated as takes after; All the inclining components speak to effectively grouped information focuses though all non slanting components speak to inaccurately arranged information focuses. For this situation, absolutely 1250 information focuses have been considered with 250 information focuses in every class. A 10 fold cross validation has been performed. There was just a single anomaly which really has a place with the class "CAV" however misclassified as the condition 'good'. On the off chance that, the misclassifications were inside the broken classes there could barely be any issues though the misclassifications were between the class "good" and any of the flawed classes then the molding method of the signs must be made more grounded and the flag procurement strategy ought to be made powerful.

6. Conclusion

In this study, the main effort has been to understand the learning rate of ELM and to compare the same with SVM

Table 1. Wavelet with learning rate SVM Vs ELM

Wavelet	Learning Time (in sec)	% Accuracy (SVM)	Learning Time (in sec)	% Accuracy (ELM)	Wavelet	Learning Time (in sec)	% Accuracy (SVM)	Learning Time (in sec)	% Accuracy (ELM)
Bior1.1	0.81	94.68	0.47	99.68	Rbio6.8	0.22	95.52	0.13	99.52
Bior1.3	0.83	95.76	0.48	99.76	Sym 2	0.17	92.84	0.10	99.84
Bior1.5	0.64	96.44	0.37	99.44	Sym 3	0.17	94.84	0.10	99.84
Bior2.2	0.59	95.84	0.35	99.84	Sym 4	0.19	95.84	0.11	99.84
Bior2.4	0.22	93.84	0.13	99.84	Sym 5	0.2	93.76	0.12	99.76
Bior2.6	0.25	94.68	0.15	99.68	Sym 6	0.22	96.84	0.13	99.84
Bior2.8	0.25	94.44	0.15	99.44	Sym 7	0.17	92.76	0.10	99.76
Bior3.5	0.66	97.68	0.38	99.68	Sym 8	0.17	89.52	0.10	99.52
Bior3.7	0.22	93.52	0.13	99.52	Meyer	0.22	94.84	0.13	98.84
Bior3.9	0.22	94.44	0.13	99.44	Coif 1	0.85	91.84	0.50	99.84
Bior4.4	0.2	95.76	0.12	99.76	Coif 2	0.62	92.84	0.36	99.84
Bior5.5	0.2	92.84	0.11	99.84	Coif 3	0.71	90.52	0.42	99.52
Bior6.8	0.2	89.44	0.12	99.44	Coif 4	0.59	98.36	0.35	99.36
Rbio1.1	0.2	94.76	0.12	99.76	Coif 5	0.6	93.44	0.35	99.44
Rbio1.3	0.2	96.84	0.12	99.84	Db 1	0.61	94.76	0.36	99.76
Rbio1.5	0.22	94.76	0.13	99.76	Db 2	0.83	95.52	0.49	99.52
Rbio2.2	0.23	95.92	0.14	99.92	Db 3	0.74	97.68	0.44	9.68
Rbio2.4	0.39	95.4	0.22	99.4	Db 4	0.25	98.84	0.15	99.84
Rbio2.6	0.22	93.84	0.13	99.84	Db 5	0.33	94.84	0.19	99.84
Rbio2.8	0.2	94.68	0.12	99.68	Db 6	0.22	93.84	0.12	99.84
Rbio3.5	0.22	95.92	0.13	99.92	Db 7	0.34	97.84	0.20	99.84
Rbio3.7	0.23	96.76	0.14	99.76	Db 8	0.19	96.84	0.11	99.84
Rbio3.9	0.22	94.76	0.13	99.76	Db 9	0.2	94.84	0.12	99.84
Rbio4.4	0.2	95.84	0.11	99.84	Db 10	0.19	92.84	0.11	99.84
Rbio5.5	0.2	93.84	0.12	99.84					

to identify the best one. The vibration signals have been extracted from the monoblock centrifugal pump and set of useful parameters were calculated using discrete wavelet transforms which formed the feature set. The classification has been separately performed with SVM and ELM with suitable orientation parameters and kernels. The classification accuracies and learning speed of both SVM and ELM were recorded and tabulated. From that table, one can suggest that the ELM algorithms could be the better choice for the classification and fault diagnosis applications. ELM could achieve a classification accuracy of 99.92% in 0.13 secs with RBIO 3.5. The % accuracy is almost close to 100% at very fast learning speed. As the learning speed has been the major challenge in machine learning, the ELM could act as a suitable alternate. However, the % accuracy 99.92 is for a particular dataset only and therefore one can consider this result as a guide map for other applications and of larger dataset size.

Table 2. Confusion Matrix

	Good	Cav	BF	IF	BFIF
Good	250	0	0	0	0
Cav	1	249	0	0	0
BF	0	0	250	0	0
IF	0	0	0	250	0
BFIF	0	0	0	0	250

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