Support Vector Machine (SVM) Based Method for Cavitation Detection In A Centrifugal Pump

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Abstract

Centrifugal pump is one type of pumps that widely used, especialy in industry. It's mechanism which cretates pressure changes usually caused cavitation. Generally, centrifugal pump fault caused by cavitation makes high noise and vibration level. Cavitation phenomenon that is not properly maintain results fatal breakdown and high economic losses. Therefore, research is needed to find and develop the method that can detect early cavitation phenomena in centrifugal pumps, and can show cavitation at several levels. An early cavitation detection can be done by vibration signal analysis using Support Vector Machine (SVM) based method. Data with sevel variety (normal, level 1, 2, and 3 cavitation) was extracted into ten statistical features. Then, it was also selected using Relief Feature Selection. In this study, two types of SVM method were used to calssify the data named binary and multi class SVM. Each multi class classification of result is optimized by Bayesian Optimization (BO) algorithm and Grid Search Method (GSM). The whole processes was carried out using Matlab R2107a. The results showed that each statistical feature contained spesific information on vibration data. Root Mean Square (RMS), Standard Deviation (SD), variance, entropy, and Standard Error (SE) are several features that showed the best plot. Feature selection process revealed that variance, RMS, and SD were the best feature to use for SVM classification. Binary SVM method showed the best plot on early cavitation with accuracy 99%. BO algorithm with multi class SVM was the best combination to classify all varieties with overall accuracy 100%.

***Keywords**:* Support Vector Machine (SVM), vibration signal, centrifugal pump, cavitation, statistical features in time domain.

1. Introduction

Centrifugal pump is one type of pump that is most widely used in the industry such as chemical, docking and shipping, also oil and gas industry because of its mechanism and construction which relatively simpler. Seeing the importance of its role, the performance is very necessary to be maintained. Reduction in its performance can be affected by fault to components by several causes. One of the most common cause is cavitation (Sukardi et al., 2012). In centrifugal pump, cavitation occurs due to the evaporation of liquid flowing fluid which is caused by a pressure drop to below the saturated vapor pressure.

This phenomenon is very important to be detected from the beginning, because a decrease in pump capacity can disrupt production activities. As experienced in the centrifugal pump 53-101 C Sungai Gerong, there was a decrease in the flow of water pumped from 2050 m^3/hour to 1925 m^3/hour (Hariady, 2014). This will certainly impact on the level of productivity in an industry, so that an effective method is needed in detecting early cavitation in centrifugal pumps.

Early cavitation detection on centrifugal pump then examined and tested by several researchers in various methods. One of which is done by Jansen and Dayton (2000) using Spectrum analysis from vibration signals. In the other hand, Al - Hasymi (2009) examined the use of statistical features in time domain detecting damage to centrifugal pump. Another method was found by Rajakarunakaran et al.,(2008) using a machine learning method, named Artificial Neural Network (ANN). Then Sakthivel et al., (2010) apply the Decision Tree algorithm in detecting cavitation in centrifugal pump. Farokhzad (2013) detected several fault of pump using the Adaptive Network Fuzzy Inference System (ANFIS), but indication of cavitation at the initial stage could not be detected due to cavitation frequency not showing high amplitude values. Some of the researches above attempt to detect cavitation before the fault occur, but cavitation at the incipient level is difficult to detect.

The researchers then tried to use one of the Pattern Recognition-based methods, called Support Vector Machine (SVM). This method is considered as the method which enable to classify data primerly and can provide information with a high level of accuracy. Research conducted in proving the accuracy level of cavitation detection results on centrifugal pumps using SVM. Samanta et al.,(2003) compared the performance of ANN with SVM, as a result that the SVM classification is more favored. Then Saberi et al. (2011) found that SVM method had the advantage of having kernel function that it could distinguish normal condition and high noise on centrifugal pump. Sakthivel et al. (2012) compared the use of Proximal Support Vector Machine (PSVM), Gene Expression Programming (GEP), Wavelet-GEP and SVM, and SVM being the best method with highest accuracy.

The use of SVM in detecting early cavitation requires the help of an important device to classify data in a linear form, known as kernel function. Selection of the right kernel function affects the detection results. In detecting cavitation in a centrifugal, the recommended kernel function is Gaussian Radial Basic Function (RBF), because RBF can classify non-linear data groups (Sakhtivel et al., 2016). In addition, the statistical features in time domain used can also affect SVM performance. Rapur & Tiwari (2016) proposed that the statistical parameters mean, standard deviation, and entropy are highly recommended because they provide accurate data information in detecting fault to centrifugal pump. On the other hand, Elangovan et al. (2011) result study proved that the recommended statistical parmeter is standard error and minimum value.

Heretofore, research and development has been carried out continuously to improve SVM performance. Syarif et al. (2016) attempted to improve the result of the SVM classification using the Grid Search Method (GSM) optimization algorithm. Recently, Kumar et al., (2017) using Genetic Algorithm (GA), managed to improve the classification accuracy. Bordoloi & Tiwari (2017) compared the optimization algorithms of GSM, GA, and Artificial Bee Colony Algorithms (ABCA). Vibration signal data recording was carried out in two places, namely the casing and bearing housing and by varying the rotational speed and blockage. The result show that optimization algorithm can affect classification accuracy.

From the previous studies, it can be seen that SVM can provide more accurate detection result. This method is also considered more effective than previous methods. Based on several previous research observation, fault detection method based on SVM centrifugal pump can outperform several other methods in terms of accuracy classification. The accuracy of SVM classification is determined based on the selection of statistical features, kernel function, and the correct optimization algorithm. The following Table 1 and Table 2 described the use of statistical features, kernel function and optimization algorithm in SVM.

Table 1 The use of Statistical Features in SVM

Year	Author (s)	Statistical Features in Time Domain
2009	Al-Hasymi	PDF, RMS, SD
2011	Ahmed, et al.	RMS, Variance, Kurtosis
2012	Sakhtivel, et al.	Standar Error, Minimum Value
2015	Luo, et al.	RMS, Crest Factor, Peak Value, PDF
2016	Al-Tobi & Al-Sabari	RMS & Peak Value
2016	Rapur & Tiwari	Mean, SD, Entropy
2017	Azizi, et al.	RMS, SD, Variance
2017	Kamiel & Ramadhan	PDF, Variance, SD, RMS
2017	Tabar, et al.	RMS & SD

Table 2 The use of Kernel Function and Optimization Algorithm in SVM

Year	Author (s)	Kernel Function	Optimization
2007	Widodo & Yang	Linear, Polynomial, RBF	(Υ, d, C) SVC
2011	Elangovan, et al.	Linear, Polynomial, Sigmoid, RBF	(v, C) SVC
2016	Syarif, et al.	Linear, Polynomial, Sigmoid, RBF	(C , Υ) SVC – GA & GSM
2016	Alshamlan, et al.	Linear, Polynomial, Sigmoid, RBF	GA, PSO, ABCA
2016	Sakhtivel, et al.	Linear, Polynomial, Sigmoid, RBF	(Υ, C) SVC
2017	Kumar, et al.	RBF	(C, Υ) SVC - GA
2017	Bordoloi & Tiwari	RBF	(C , v) SVC – GA, ABCA, GSM

However, there is no standard provision in determining the use of kernel function, statistical parameter, and the best optimization algorithm for detecting cavitation in centrifugal pump. Further research and development of this method can be done to get an optimum result. Therefore, this study aims to find the best combination of kernel function, statistical features, and optimization algorithm in SVM to detect early cavitation and to classify several level of cavitation in centrifugal pump.

2. Support Vector Machine

SVM is one of method that classify data based on pattern recognition. Pattern recognition works with separating data into a number of groups or classes (Theodoridis, 2003). This method can be classified as part of an artificial intelligence system built for decision making. Input data used is various, such as numbers, images, sounds, or a signal wave. This method is very popular in the field of statistic. Up to now, the implementation of the analysis vibration signal method based on pattern recognition continues to develop. This affects in the increasing number of new methods based on pattern recognition. The appearance of this new method indicates that the level of popularity in the future will be even better

SVM is a method which basically used for binary classification (Cortez and Vapnik, 1995). The first time SVM found by combining several sets of concepts in the field of pattern recognition. Basically, this method works by finding the best hyperplane that separates groups of data on a dimension perfectly into two classes (Gunn, 1998).

The pattern of the two classes assumed, have been completely separated by a hyperplane in a dimension defined by equation (1).

$$\vec{w}.\vec{x} + b = 0 \quad (1)$$

If $\vec{x_i}$ in class -1, then as shown in equation (2).

$$\vec{w}.\vec{x_i} + b \leq -1 \quad (2)$$

While the value $\vec{x_i}$ in class +1, was shown in equation (3).

$$\vec{w}.\vec{x_i} + b \geq +1 \quad (3)$$

Quadratic Programming (QP) problem is an effort to maximize the value of the distance between the hyperplane and its closest point by finding its minimum point like equation (4).

$$\min_{\vec{w}} \tau\,(w) = \frac{1}{2}\ \|w\|^2 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (4)$$

$$y_i\ (\vec{x}_i . w + b) - 1 \geq 0, \forall_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (5)$$

The problem in equation (4) and (5) can be solved by the Lagrange Multiplier (α_i) technique, as in the following equation (6).

$$L\ (\vec{w}, b, \alpha) = \frac{1}{2}\|\vec{w}\|^2 - \sum_{i=1}^{l} \alpha_i \left(y_i \left((\vec{x_i} .\ \vec{w} + b) - 1 \right) \right); (i = 1,2, \ldots\ldots, l) \ldots. (6)$$

Furthermore, equation (4) was optimized by maximizing problem that only contained value (α_i), as in the following equation (7).

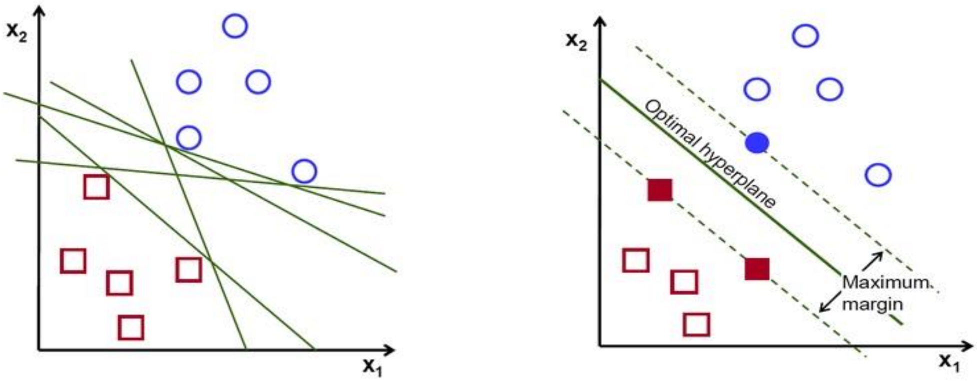
$$\sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{l} \alpha_i \alpha_j y_i y_j x_i x_j \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (7)$$

So, the equation (8) is obtained:

$$\alpha_i \geq 0 (i = 1,2, \ldots\ldots, l)\ \sum_{i=1}^{l} \alpha_i y_i = 0 \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (8)$$

From equation (8) showed that the value (α_i) is mostly positive, and support vector correlates with this positive value (α_i).

In Figure 1 (a) showed several patterns of two classes (the pattern in class A is marked with a red box symbol and the pattern in class B is marked with a blue circle symbol) which further be processed to search for the best hyperplane by giving rise to several discrimination boundaries (alternative split lines). In determining the best hyperplane, it can be done by finding the maximum point and measuring the margin. Figure 1 (b) showed the best hyperplane located in the middle between the two classes, and the pattern near the hyperplane is Support Vector.



a b

Figure 1 (a) Search for optimal hyperplane, **(b)** Optimal separating hyperplane

3. Grid Search Method (GSM)

GSM is a method which based on grid searching in a mapping. Commonly, a mapping function works by forming an imaginary decision boundary of data group. The decision boundary is created based on the value of each classification parameter. The GSM algorithm attempts to create a grid from each mapping point, then the grid evaluates the value of the classification parameter that produced (Wenwen, 2014). In each evaluation result, the GSM algorithm lists the best parameter value and reuses them as optimized result.

The grid position on the optimization result in one iteration will be the reference used in the next iteration process. On the other words, each grid formed in the entire optimization process has a correlation with each other. This affects the optimized mapping function and it will show different mapping results from before. In order to obtain optimal result, this method must evaluate all of the existing mapping points. Therefore, the number of grids produced will also be in accordance with the number of samples mapped. Those affect the GSM algorithm difficult to apply for mapping in high dimension, because it will provide inconsistent optimization result.

4. Bayesian Optimization (BO)

The basic principle used in the BO algorithm is evaluating an objective function where the minimum values possessed in the function are evaluated and returned in an optimal form. This method has two main functions, consist of the acquisition function and optimization function (Mockus et al, 1994). The BO acquisition algorithm function can be defined as a search function. This function is to find out the objective function that is less than optimal. According to Snoek et al., (2012), an objective function is categorized as not optimal if it has a parameter value below the standard set by the acquisition function. Thus, the acquisition function will look for a number of objective functions that fall into the sub-standard category. Every objective function evaluated is then optimized using the optimization function by building artificial sampling based on the best probability.

5. Methods

This research was done by several step as shown in Figure 2. The data acquisition process was done by generating 500 files data from vibration signal in every four variations of conditions, including normal (0^{o} valve blockage), level 1 cavitation (720^{o} valve blockage), level 2 cavitation (1440^{o} valve blockage), and level 3 cavitation (2160^{o} valve blockage). The time span needed for the acquisition process for 10 seconds per file and pause for 2 seconds.

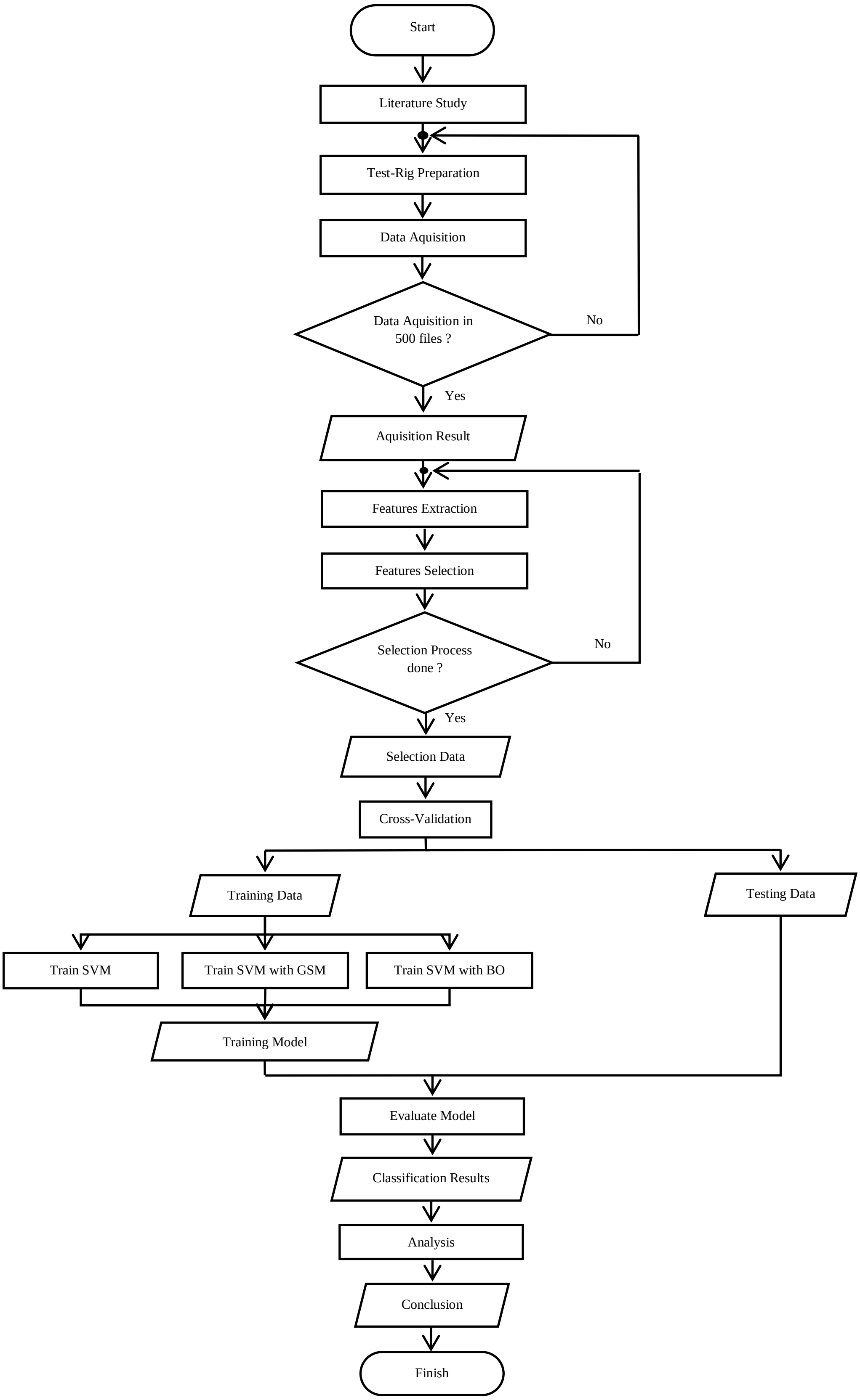
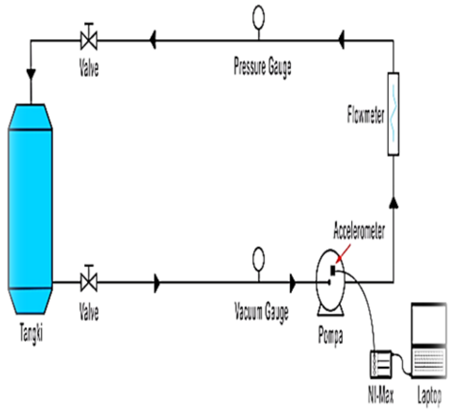


Figure 2 Research Flowchart

The pump rotational speed was regulated at 2850 RPM and a sampling rate of 17066 Hz to produce a stable change in each conditions. This process was carried out using the NI 9234 acquisition device, Chassis NI DAQ 9174, and accelerometer. The data acquisition process was regulated using the NI MAX and MATLAB R2017a software on a laptop connected to an acquisition device.

5.1 *Cavitation Test-Rig*

Cavitation rig is the device used in investigating cavitation phenomena occur in centrifugal pumps. The design of this rig was done in such a way so that the research conducted could provide appropriate result, and would obtain the best method in detecting the occurrence of early cavitation. Cavitation rig was a water pump installation consisting of several components. In the process this device would work like a water pump installation in general, after that the vibration signal recording processed on the pump was carried out using an accelerometer. The cavitation test-rig section can be seen as shown in Figure 3.



(a) **(b)**

Figure 3 **(a)** Cavitation Test-Rig, **(b)** Workflow Scheme

5.2 *Feature Extraction & Selection Process*

The results of the acquisition data were extracted into 10 statistical features in time domain as shown in Table 3. Each statistical features that generated and then plotted to show each of its characteristics to the distribution of data from vibration signal of all conditions. All results of extraction process where then selected. The feature selection process was done by using Relief Feature Selection. This method ranked the statistical features based on the weight of the information content. The feature selection process then produced the best data input for SVM classification.

Table 3 Statistical Features in Time Domain

Statistical Features in Time Domain	**Formula**
Root Mean Square (RMS)	$\sqrt{\frac{1}{n}\sum_{i=1}^{N}(x_i - \bar{x})^2}$
Standar Deviation (SD)	$\sqrt{\frac{\sum_{i=1}^{N}(x_i - \bar{x})^2}{N-1}}$
Peak Value	$\max\lvert x\ (N)\rvert$
Kurtosis	$\frac{\sum_{i=1}^{N}(x_i - \bar{x})^4}{(N-1)\ \sigma^4}$
Variance	$\frac{(x_i - \bar{x})^2}{N-1}$
Crest Factor	$\frac{\max(\lvert x\ (n)\rvert)}{\sigma}$
Mean	$\frac{1}{K}\sum_{k=1}^{K} x\ (k)$
Entropy	$\sum_{i=1}^{N} p\ (x_i)\ \log_{10} p(xi)$
Minimum Value	$\min\lvert x\ (N)\rvert$
Standard Error (SE)	$\sqrt{\frac{1}{(n-2)} - \left[\sum(y-\bar{y})^2 - \frac{[\sum(x-\bar{x})(y-\bar{y})]^2}{(x-x^2)^2}\right]}$

5.3 *Classification Process*

The classification stage was carried out using the SVM-based method. To determine the various levels of cavitation and the initial formation, two methods were applied, namely Binary and Multi Class SVM. Kernel Function for mapping process used Radial Basis Function (RBF). The multi-class SVM classification method was carried out with three trials and was equipped with an optimization method. The optimization method used at this stage was based on Grid Search Method (GSM) and Bayesian Optimization (BO) techniques.

GSM algorithm is an optimization technique based on grid search. Grid search is performed on each mapping function. Each mapping function with optimal results and not optimal will be evaluated by the GSM algorithm, so that the number of evaluations produced is a number of mapping processes that occur. The results of optimization then be sorted according to functions that have the best classification parameters.

BO techniques were carried out to evaluate any mapping errors that found out. This technique was equipped with an acquisition function that was useful for determining which mapping function were not optimal. Then the mapping function was optimized and would be returned in the training process. The number of mapping function evaluated according to the number of mapping error processes occured.

6. Results & Discussion

6.1 *Characteristic of Statistical Features In Time Domain*

Statistical feauters in time domain extraction aimed to find out various characteristics of data from vibration signal generated under normal condition, level 1, 2 and 3 cavitation. Each result obtained from all statistical features showed a different plot. This was as shown in Figure 4.

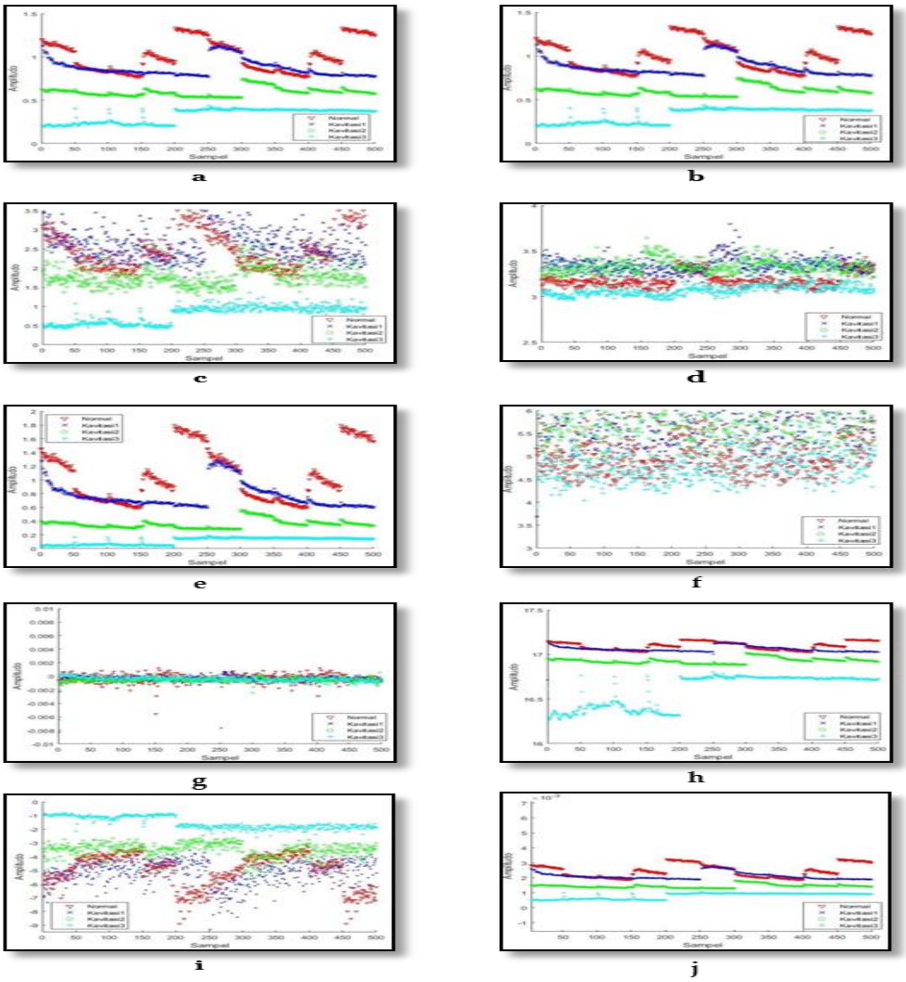


Figure 4 (a) RMS, **(b)** SD, **(c)** Peak Value, **(d)** Kurtosis**, (e)** Variance, **(f)** Crest Factor, **(g)** Mean, **(h) Entropy**, **(i)** Minimum Value**, (j)** SE

Some features such as RMS, SD, variance, entropy, and SE almost showed the separation of the four vibration signal data completely. But on normal data and level 1 cavitation, it has not been able to show the optimal result. Thus, the selection process was intended to select the best features which used as input for SVM classification. The result of features selection using Relief Feature Selection can be seen in Figure 5.

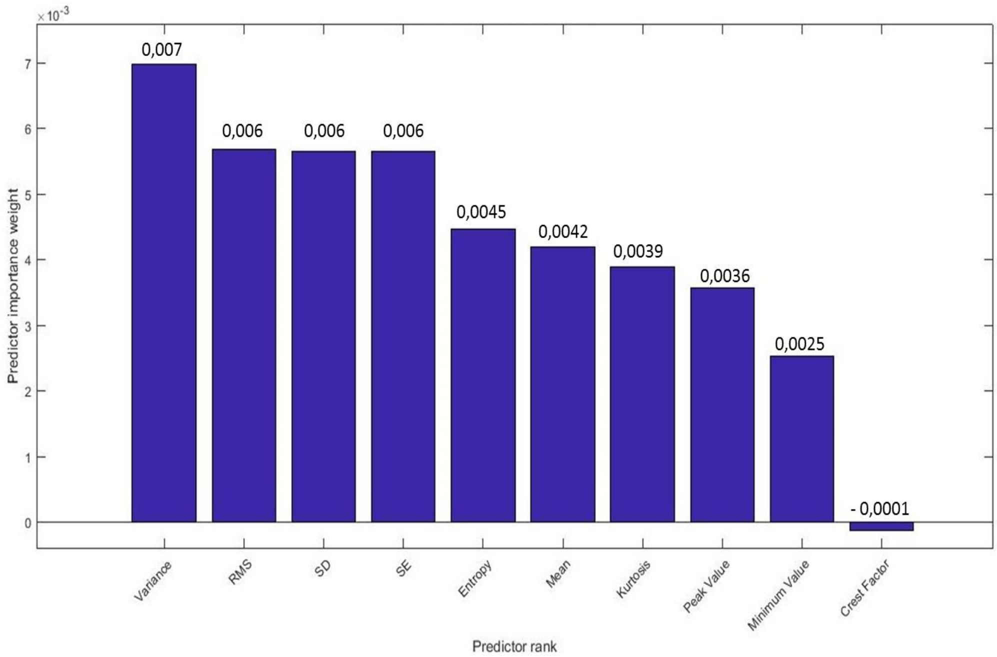
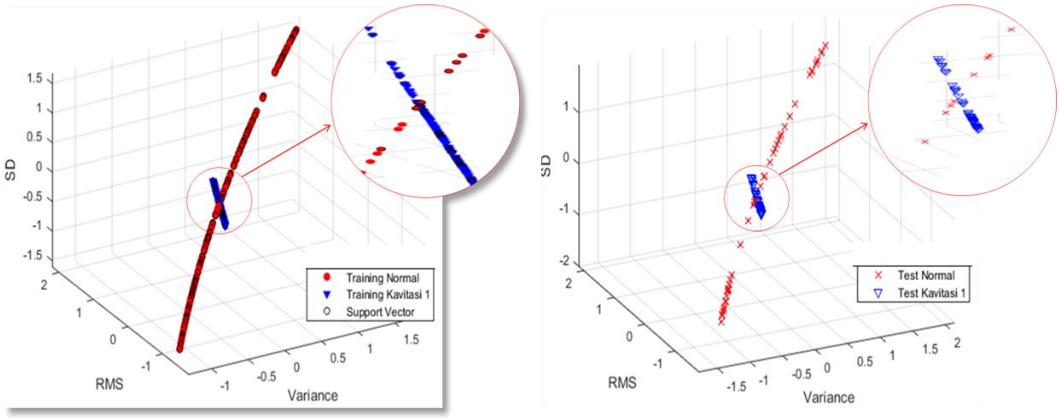


Figure 5 Features Selection Result

The results of the selection showed the variance with the highest weight and the opposite crest factor. The three highest order features were used as classification input because they contained a weight of more than 0.0050. SE was not used as input because it had the same value as SD. In addition, the use of three parameters would produced better visualization in classification results.

6.2 *Binary Classification*

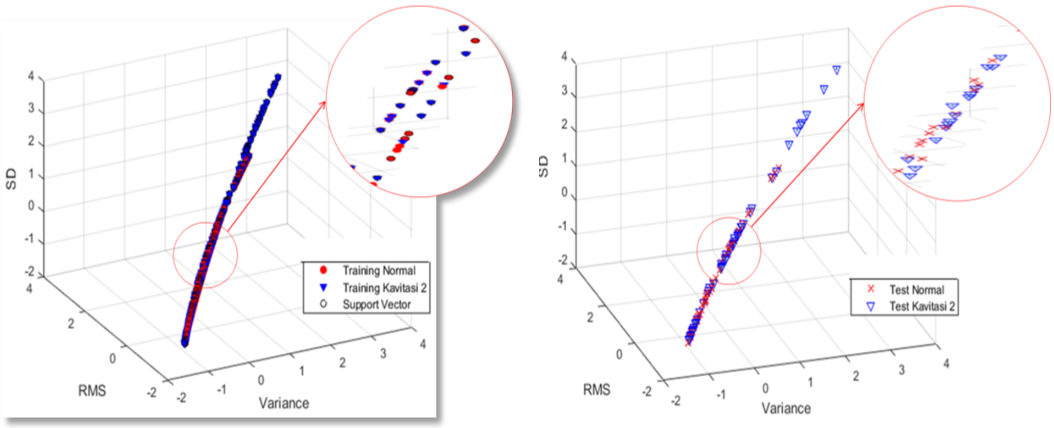
The binary SVM classification was performed on normal data on all three cavitation level. Data input for each process was 100 data x 3 statistical features. The two main stages carried out in this classification were the training and testing process. Training was intended to form a classification model and generated mapping function, while testing was done to evaluate the training model and determine accuracy. The total input data was separated using the cross validation process. This process elaborated a number of 800 data as training data, and 200 data were used for the testing process. The classification results were shown in Figure 6 until 8.



a

b

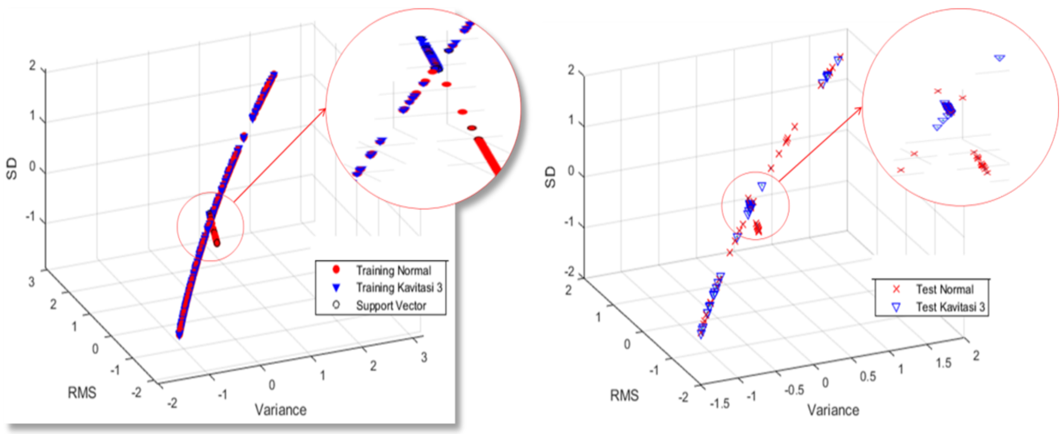
Figure 6 Normal and Level 1 Cavitation **(a)** Training, **(b)** Testing



a

b

Figure 7 Normal and Level 2 Cavitation **(a)** Training, **(b)** Testing



a

b

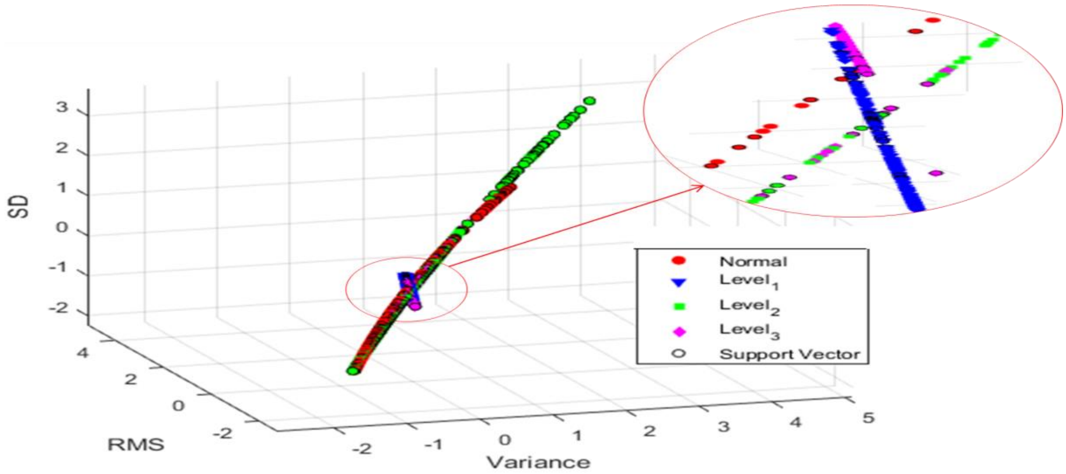
Figure 8 Normal and Level 3 Cavitation **(a)** Training, **(b)** Testing

In the plot, it could be seen that each result showed a different pattern distribution. This was because of the data in each variation of condition had a different amplitude.

6.3 *Multi-Class Classification*

The steps taken in the multi class SVM almost corresponded to the binary SVM method. This method classified the four variations of conditions and showed the result of the spread of the pattern. The total data input which owned was 2000 data x 3 statistical features. The cross validation process produced 1800 training data and 200 testing data, where all variations had the same amount of data in each set.

Classification was done by three experiments, those were muti class SVM without optimization, using GSM optimization, and BO algorithm. From these three experiments, the highest level of accuracy was shown by a combination of multi class SVM and BO. The classification result were shown as in Figure 9.



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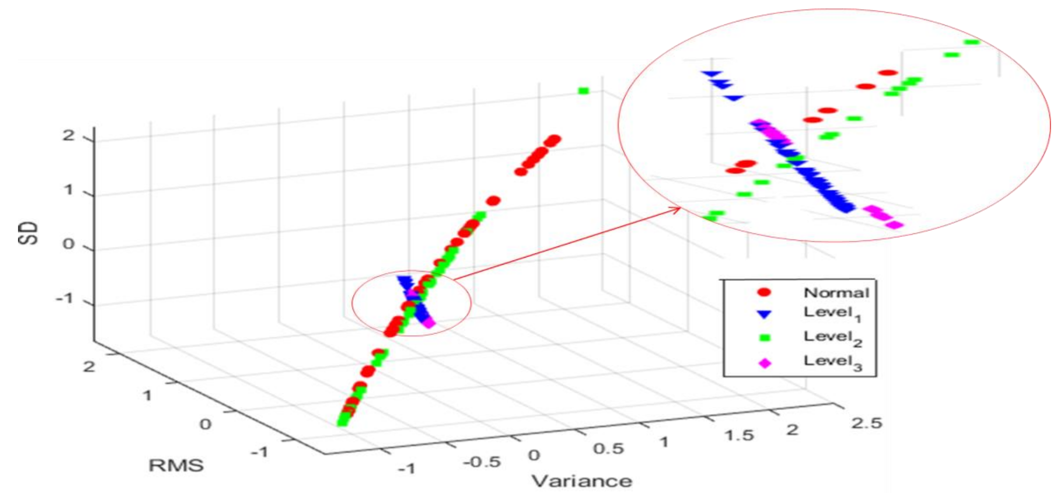

b

Figure 9 Multi Class Classification SVM using Bayesian Optimization **(a)** Training, **(b)** Testing

The accuracy of the multi class SVM and BO classification were explained in the confusion matrix as in Figure 10.

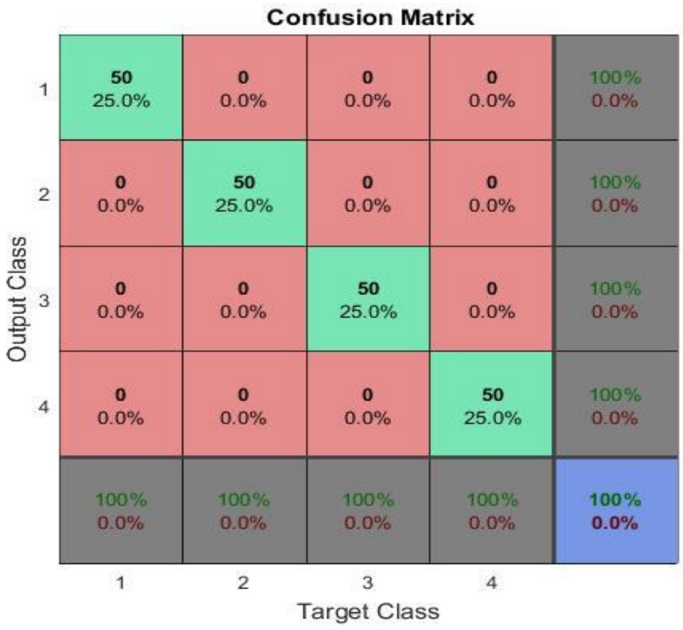

Figure 10 Confusion Matrix of Multi Class Classification SVM using Bayesian Optimization

6.4 *Summary*

This research was conducted in several experimental stages. Each stage showed the results of differences in each variation of condition. The following Table 4 until 8 showed the summary of the result.

Table 4 Data Acquisition Result

Variety	**Blockage (°)**	**Pump Speed (RPM)**	**Sampling Rate (Hz)**	**Flow Rate (*l*/m)**	**Discharge Press. (bar)**	**Suction Press. (bar)**
Normal	0	2850	17066	110	0.7	0.1
Level 1	720	2850	17066	110	0.8	0.12
Level 2	1440	2850	17066	102.5	0.8	0.22
Level 3	2160	2850	17066	60	1.2	0.4

Table 5 Statistical Features Analysis Result

Statistical Fefatures in Time Domain	**Analysis Results**
RMS, SD, Variance, Entropy, & SE	Show class differences correctly, but can not show significant differences in normal condition and level 1 cavitation.
Peak Value & Kurtosis	It can hardly separate data group from each variation properly. Only data level 3 cavitation can be separated properly.
Crest Factor, Mean, & Minimum Value	Completely unable to separate data group in four variations.

Table 6 Features Selection Result

Ranked	Statistical Features in Time Domain	Weight
1	Variance	0,006974609
2	RMS	0,005680424
3	SD	0,005646849
4	SE	0,005646849
5	Entropy	0,004460221
6	Mean	0,004190307
7	Kurtosis	0,003894734
8	Peak Value	0,00356323
9	Minimum Value	0,002523585
10	Crest Factor	-0,000132408

Table 7 Binary SVM Result

No	Binary SVM	Accuracy (%)
1	Normal and Level 1	99
2	Normal dan Level 2	97
3	Normal dan Level 3	100

Table 8 Multi Class SVM Result

Method	Pump Condition	Missclassification	Accuracy	Overral Accuracy
Multi Class SVM (without Optimization)	Normal	23	13,50%	58%
	Level 1	13	18,50%	
	Level 2	15	17,50%	
	Level 3	33	8,50%	
Multi Class SVM (GSM Optimization)	Normal	0	25%	99,50%
	Level 1	0	25%	
	Level 2	1	24,50%	
	Level 3	0	25%	
Multi Class SVM (Bayesian Optimization)	Normal	0	25%	100%
	Level 1	0	25%	
	Level 2	0	25%	
	Level 3	0	25%	

Table 4 explained the result of the flowrate, suction and discharge pressure of each variation. In table 5 showed that some statistical features such as RMS, SD, variance, entropy, and SE almost separated the four conditions variation completely. However, these two results could not be the main reference in detecting cavitation phenomena because they have not shown optimal results, especially in the detection of early cavitation. So that further analysis needs to be done to get optimal results.

The results of data selection in Table 6 showed the confirm that it was in line with the distribution of statistical features data. In table 7 showed the success of SVM binary classification in detecting early cavitation phenomena, with an accuracy of 99%. The separation of the four classes were perfectly carried out on a combination of multi class SVM and BO as in Table 8 with an accuracy of 100%.

The results of this study revealed that the SVM-based cavitation detection method was enable to show the early cavitation phenomenon completely. The combination of SVM-BO algorithm was the most superior method to detect cavitation in several levels.

7. Conclusions

The result and discussion in this study indicated that the characteristic of each statistical feature in time domain produced specific information to the vibration signal distribution. RMS, SD, and variance are the best statistical features used as input for SVM classification. SVM classification method has been proven to detect early cavitation phenomena in centrifugal pump. This was shown in the classification between normal and level 1 cavitation which produced an accuracy of 99%. Development and optimization of SVM multi class algorithms by using BO was the best combination method in detecting cavitation at several levels. The level of accuracy obtained in this method was 100%.

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September 4th, 2018

Program Studi Teknik Mesin

Lembar Persetujuan Naskah Publikasi dan Abstrak Skripsi

Judul Skripsi:	**METODE DETEKSI KAVITASI BERBASIS *SUPPORT VECTOR MACHINE (SVM)* PADA POMPA SENTRIFUGAL**
Judul Naskah Publikasi:	Metode Deteksi Kavitasi Berbasis *Support Vector Machine (SVM)* pada Pompa Sentrifugal
Nama Mahasiswa:	**Muhammad Taufiq Akbar**
NIM:	**20140130069**
Pembimbing 1:	**Berli Paripurna Kamiel, S.T.,M.M.,M.Eng.Sc., Ph.D.**
Pembimbing 2:	**Dr. Bambang Riyanta, S.T., M.T**

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☐ Abstrak berbahasa Indonesia ☐ Naskah Publikasi ☐ .... ☐ ....

☐ Abstrak berbahasa Inggris ☐ .... ☐ .... ☐ ....

*beri tanda √ di kotak yang sesuai

Muhammad Taufiq Akbar *Tanggal, 30 Agustus 2018*

Persetujuan Dosen Pembimbing dan Program Studi

☑ Disetujui

Berli Paripurna Kamiel, S.T., M.M., M.Eng.Sc., Ph.D *Tanggal, 30 Agustus 2018*

Berli Paripurna Kamiel, S.T., M.M., M.Eng.Sc., Ph.D *Tanggal, 30 Agustus 2018*