Diagnosis of Induction Motor Faults Based On Current and Vibration Signals Using Support Vector Machine Model

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Abstract. Early fault diagnosis of the induction motor can prevent sudden failure of the motor, which implies loss of production and sometimes brings safety problems. The purpose of this paper is to explore a method for induction motor fault diagnosis using a support vector machine model. The raw current and vibration signals are pre-processed using variational mode decomposition to eliminate the noise. Eight features in the time domain are extracted from the signals. These features are then evaluated using principal component analysis to reduce their dimension. Two principal components that cover 95\% of the variance of the data are used as predictors in the SVM model. SVM models with different types of kernels are evaluated for their performance. The results show that the current signals give better accuracy in diagnosing induction motor faults than the vibration signals. The current signals perform very well at all speeds and in all types of motors. Their accuracy is 100\% for training and testing data. Meanwhile, the accuracy of the vibration signal in diagnosing the motor faults is good at speeds of 749 rpm, and the diagnosis accuracy decreases at speeds of 1499 rpm.

1 Introduction

The invention of induction motors in the 1800s heralded the beginning of their use in modern industrial environments. The interaction of the revolving magnetic field and the rotor converts electrical energy into mechanical energy in these motors [1]. Induction motors have various advantages, including their simple design, low production costs, ease of maintenance, high efficiency in ordinary operating circumstances, and dependable operation [2]. Nevertheless, extended and consistent operation can lead to the emergence of issues within the components of induction motors. These problems arise primarily from the unavoidable friction, which generates excessive heat in different motor parts [3]. Such faults in induction motors can be categorised into two main types: mechanical and electrical [4]. These faults may manifest independently or occur simultaneously. Among the typical types of faults encountered, bearing faults constitute approximately 41\%, stator faults make up 37\%, rotor faults account for 10\%, and the remaining 12\% consist of other types of faults [5].

As a result, early detection is critical for proactively avoiding unforeseen problems in induction motor components. Incorporating such preventative measures is critical, especially when developing maintenance strategies to ensure continuous and flawless operations in modern industrial processes [6] [7]. In order to accomplish this, several monitoring systems can be used to examine the state of the machinery and identify any possible problems before they become serious problems [4].

There are three approaches to implementing such monitoring methods. Firstly, the model-based approach utilises mathematical modelling. Secondly, the signature extraction approach involves extracting signals such as vibrations, temperatures, sounds, loads, and currents in the time and/or frequency domain from the operating motor. Lastly, the knowledge-based approach builds upon conventional methods and often employs artificial intelligence to apply predictive maintenance techniques [7].

Numerous artificial intelligence techniques are employed in predictive maintenance, including Expert Systems (ES), Artificial Neural Networks (ANNs), Fuzzy Logic Systems (FLS), Genetic Algorithms (GAs), and Support Vector Machines (SVM) [8]. Among these methods, the SVM approach has gained widespread popularity and is currently the preferred choice. This preference is mainly attributed to its excellent predictive performance and its ability to minimize training and testing times, thus reducing the processing load during analysis [3]. The SVM method is particularly well-suited for diagnosing faults in rotating machines that experience faults caused by excessive vibration. As a result, it is extensively used for damage diagnosis and for classifying the various types of damage that may occur in such machines [9].

The predictors that feed the SVM model influence its accuracy and efficacy. The predictors, also known as features, are retrieved and chosen from the measured signals. The signal is represented by the features. These can be signal statistical metrics like mean, median, rms, variance, kurtosis, skewness, and so on. The measuring signal is frequently mixed with noise. As a result, the
derived features lose the key information regarding the health of the motor. To overcome the noisy signal, some researchers propose to decompose the signals into their components using discrete wavelet transform [10], [11]. The others use empirical mode decomposition to eliminate the effect of the noisy signals [12], [13]. A relatively recent and advanced method used for signal decomposition is Variational Mode Decomposition (VMD). By applying VMD as the decomposition step, the raw signal can be effectively broken down into its constituent components [14]. These resulting signals, obtained through VMD, are then utilized for further analysis and classification using SVM, leading to more accurate and reliable fault detection and diagnosis.

The extraction of features that effectively capture the properties of the signal is required for the diagnosis of rotating machine states. However, not all statistical variables are equally appropriate for correctly defining damage patterns, and using too many of them can raise the computational cost. To overcome this, it is critical to carefully choose the most significant statistical features and minimise the data's total dimensionality. Principal Component Analysis (PCA) is one method for accomplishing this. PCA assists in finding and maintaining the most important features while eliminating those that are less relevant, simplifying the data, and optimising the analysis process [15].

The most common signals used to monitor induction motor health are vibration and current signals. Therefore, the aim of this paper is to apply a support vector machine model to diagnose induction motor faults using vibration and current signals. The raw signals will be decomposed using the variational mode decomposition method to eliminate noisy signals.

2 Methodology

The data for the induction motor faults is taken from the induction motor test rig, as shown in Fig. 1. The test rig consists of a 2-hp induction motor, an inverter, and an AC voltage regulator.

![Induction motor experimental test rig](image)

In this test, artificial faults are given to the bearing and stator of the induction motor to simulate the real situation. Artificial defects in the bearing are created by drilling a 1 mm hole in the outer race using electrical discharge machining (EDM), while artificial defects in the stator are induced by applying a 10% voltage drop to one of the phases using an AC Voltage regulator. The motor was operated at two different speeds: 749 and 1499 rpm.

The data are picked up at a rate of 1 second every 5 minutes. The data are sampled at 20.000 Hz. 300 data sets are collected for each motor condition. As a result, it obtained 900 samples total. The data will then be divided into training data and testing data in an 80% to 20% ratio.

2.1 Characterization of Natural Zeolite

Data preprocessing is the first step in processing the data obtained from the measurement. The raw signals are decomposed using variational mode decomposition (VMD). The purpose of this is to reduce unnecessary external signals through the selection of intrinsic mode functions (IMFs) with the highest relative energy value. The VMD is performed because the signals generated in this experiment exhibit patterns of non-stationary or semi-stationary conditions with a more limited frequency variation. Fig. 2 shows preprocessing data using VMD on current and vibration signals.

![Preprocessing data using VMD on current and vibration Signals](image)

2.2 Characterization of Natural Zeolite

Feature extraction is a crucial step in selecting statistical features that have a significant impact on the data analysis to be conducted. The selection of statistical features is essential as it can enhance the accuracy of both the training and testing data, reduce overfitting, improve computational efficiency, and eliminate irrelevant or noisy features in the statistical analysis. The statistical features used include Crest Factor (CF), Kurtosis (Kur), Mean, RMS, Skewness (Sk), Standard Deviation (Std), Variance (Var), and Peak to Peak (P2P). The eight statistical features are used because they are considered to represent each characteristic of a given artificial fault variation.

Then, to aid in understanding the relationship between statistical features, a step was taken in the form of varying the number of statistical features. This step was taken to provide information about the dataset's characteristics across different numbers of features, identify patterns or trends for each variation in the number of features, and assist in evaluating the performance of the model on both the training and testing datasets for each variation in the number of features. These features are evaluated in stages, starting with the use of a total of 4 features and increasing to a
total of 8 features. The feature composition is described in Table 1.

Furthermore, the results of each change in the number of feature extractions are processed to minimise the dimensions of the data using the Principal Component Analysis (PCA). The goal is to minimise the data dimensions of each feature variation by projecting each connected variable in the original dataset onto a lower-dimensional space. The Principal Component (PC) produced as a result of this feature selection has the proportion of variance in each PC produced. This study employs two PCs, PC1 and PC2, with values more than 95%, which are subsequently employed as predictors in the classification procedure.

<table>
<thead>
<tr>
<th>Number of Feature</th>
<th>Statistic Feature</th>
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</thead>
<tbody>
<tr>
<td>Feature</td>
<td>Kurtosis (Kur), Mean, Skewness (Sk), Standar Deviasi (Std)</td>
</tr>
<tr>
<td>5 Feature</td>
<td>Crest Factor (CF), Kurtosis (Kur), RMS, Skewness (Sk), Standar Deviasi (Std)</td>
</tr>
<tr>
<td>6 Feature</td>
<td>Crest Factor (CF), Kurtosis (Kur), Mean, RMS, Skewness (Sk), Varians (Var)</td>
</tr>
<tr>
<td>7 Feature</td>
<td>Crest Factor (CF), Kurtosis (Kur), Mean, RMS, Skewness (Sk), Standar Deviasi (Std), Peak to Peak (P2P)</td>
</tr>
<tr>
<td>8 Feature</td>
<td>Crest Factor (CF), Kurtosis (Kur), Mean, RMS, Skewness (Sk), Standar Deviasi (Std), Varians (Var), Peak to Peak (P2P)</td>
</tr>
</tbody>
</table>

2.3 Support Vector Machine

The implementation of the Support Vector Machine (SVM) classification method to diagnose faults in induction motors provides a solution for the challenge of fault classification involving more than two classes. SVM offers the capability of handling multiclass classification tasks through the application of the One vs. One technique. This technique is widely adopted for classifying data by constructing separate SVM models for each class. By using this approach, the SVM models are then tested on the respective class data, enabling efficient and accurate classification of multiple fault types in induction motors.

The data for each type of class is divided into training data (TRD) and testing data (TED) with a percentage of 80% and 20%, respectively. The purpose of dividing the data is to ensure that the SVM model can generalize to each type of data. The training data are used to build and train the SVM model, while the testing data are used to test the SVM model's ability to classify the data that has been formed in the training data.

The classification using various forms of SVM is conducted by considering different feature variations and SVM kernel types, which include linear (SVM-L), quadratic (SVM-Q), cubic (SVM-C), fine Gaussian (SVM-FG), medium Gaussian (SVM-MG), and coarse Gaussian (SVM-CG) kernels. Each kernel function yields its own accuracy for classification, allowing for the identification of the most effective model based on kernel selection. Subsequently, the accuracy results for classifying the condition of the induction motor's damage are analyzed, and an error analysis is performed by comparing the outcomes obtained from training data and testing data.

3 Result and Discussion

This research examines the application of SVM model to diagnose the induction motor faults using current and vibration signals. It will cover a comparative analysis of current signals and vibration signals acquired at two distinct operating speeds. The subsequent investigation revolves around assessing the accuracy of various SVM kernels while also taking into account the utilization of different statistical features. The primary objective is to identify the most optimal number of statistical features that yield the best performance for the diagnosis of induction motor faults. By conducting a comprehensive comparison of both types of signals and exploring various SVM kernel options, the study aims to determine the most effective combination of features and classifiers to enhance the accuracy and reliability of motor fault diagnosis in real-world applications.

3.1 Current Signal

Fig. 3 shows the current signal at a speed of 749 rpm, while Fig. 4 shows the current signal at a speed of 1499 rpm.

Fig. 3. Current signal at a speed of 749 rpm

Fig. 4. Current signal at a speed of 749 rpm
3.1.1 Speed of 749 rpm

The motor condition is divided into three classes. They are normal motor, motor with bearing fault, and motor with stator faults. The results of the SVM classification for a single fault 3 classes using current signal at a speed of 749 rpm with linear kernel can be seen in Fig. 5 as follows.

![Fig. 5. Scatter plot of single fault 3 classes on current signal at 749 rpm](image)

The induction motor with normal condition are shown in the orange circle. The motor with bearing faults are shown in blue colour, and the motor with stator faults are shown in red colour. It can be seen that the model can separate the motor well. To show the accuracy of the classification, the training data confusion matrix is shown in Fig. 6 as follows.

![Fig. 6. Confusion matrix training data of single fault 3 classes on current signal at 749 rpm](image)

Table II shows good results in each SVM kernel and the use of each number of features. The SVM classification accuracy shows a value of 100% on training data and data testing. This shows that the SVM model is able to effectively predict and classify data with a very high success rate.

Table 2. SVM Single Fault 3 Classes on Current Signal at 749 RPM

<table>
<thead>
<tr>
<th>Kernel</th>
<th>4 Feature</th>
<th>5 Feature</th>
<th>6 Feature</th>
<th>7 Feature</th>
<th>8 Feature</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TRD (%)</td>
<td>TED (%)</td>
<td>TRD (%)</td>
<td>TED (%)</td>
<td>TRD (%)</td>
</tr>
<tr>
<td>SVM L</td>
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<td>100</td>
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<tr>
<td>SVM M-Q</td>
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<tr>
<td>SVM M-C</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>SVM M-FG</td>
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<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>SVM M-MG</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
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</tr>
<tr>
<td>SVM M-CG</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

3.1.2 Speed of 1499 rpm

The results of the SVM classification for a single fault 3 classes on current signal at a speed of 1499 rpm are carried out for various kernel functions which can be seen in Fig. 8 as follows.
The scatter plot in Fig. 8 shows the SVM classification using a linear kernel. Induction motors with normal conditions are shown in orange, induction motors with bearing faults are shown in blue and induction motors with stator faults are shown in yellow. It can be seen that the kernel function can separate the models well. To show the accuracy of the classification, the training data confusion matrix is shown in Fig. 9 as follows.

The scatter plot of single fault 3 classes on current signal at 1499 rpm

![Fig. 8. Scatter plot of single fault 3 classes on current signal at 1499 rpm](image)

The confusion matrix training data in Fig. 9 shows a model that has an accuracy of 100%. It can be seen that under normal conditions, bearing faults and stator faults do not occur data errors. Then, the model is tested using the testing data shown in Fig. 10 as follows.

![Fig. 9. Confusion matrix training data of single fault 3 classes on current signal at 1499 rpm](image)

The confusion matrix testing data in Fig. 10 shows an accuracy of 100%. It can be seen that the results of data testing under normal conditions, bearing faults and stator faults do not occur data errors.

Furthermore, the results of SVM classification with various type of Kernel are presented in Table III.

### Table 3. SVM Single Fault 3 Classes on Current Signal at 1499 RPM

<table>
<thead>
<tr>
<th>Kernel</th>
<th>4 Feature TRD (%)</th>
<th>4 Feature TED (%)</th>
<th>5 Feature TRD (%)</th>
<th>5 Feature TED (%)</th>
<th>6 Feature TRD (%)</th>
<th>6 Feature TED (%)</th>
<th>7 Feature TRD (%)</th>
<th>7 Feature TED (%)</th>
<th>8 Feature TRD (%)</th>
<th>8 Feature TED (%)</th>
</tr>
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<tr>
<td>SV M-L</td>
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<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
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<tr>
<td>SV M-Q</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>SV M-C</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>SV M-FG</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>SV M-MG</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>SV M-CG</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
<td>100</td>
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<td>100</td>
</tr>
</tbody>
</table>

Table III shows good results in each SVM kernel and the use of each number of features. SVM classification accuracy shows a value of 100% on training data and testing data. This shows that the SVM model is able to effectively predict and classify data with a very high success rate.

Discussion on diagnosing induction motor fault by determining the optimal number of features visualized on a bar chart. Each signal data contains average accuracy information at 749 rpm speed and 1499 rpm speed. Fig. 8 shows average accuracy of single fault 3 classes on current signals.
Fig. 11 shows the maximum accuracy in using the total feature variation of up to 100% on all types of SVM kernels. This indicates optimal performance in classifying using SVM on current signals.

In this research, a 100% accuracy was achieved by employing current signal analysis at two different speeds. This highlights the effectiveness of combining VMD PCA and SVM techniques for accurately classifying single mechanical and electrical faults in induction motors, outperforming the 97.6% accuracy attained by Ali et al. [7] using a fine Gaussian kernel. This study underscores the superior performance and potential of the proposed approach in fault classification for induction motors.

3.2 Vibration Signal

Fig. 12 shows the vibration signal at a speed of 749 rpm, while Fig. 13 shows the vibration signal at a speed of 1499 rpm.

The results of the SVM classification for a single fault 3 classes on vibration signal at a speed of 749 rpm using cubic SVM is shown in Fig. 14.

The scatter plot in Fig. 14 shows that the motor data with different conditions can be separated clearly. Induction motors with normal conditions are shown in orange, induction motors with bearing faults are shown in blue, and induction motors with stator faults are shown in yellow. Models that experience data errors are in the stator fault class. To show the accuracy of the classification, the confusion matrix is shown in Fig. 15.

The scatter plot in Fig. 14 shows that the motor data with different conditions can be separated clearly. Induction motors with normal conditions are shown in orange, induction motors with bearing faults are shown in blue, and induction motors with stator faults are shown in yellow. Models that experience data errors are in the stator fault class. To show the accuracy of the classification, the confusion matrix is shown in Fig. 15.
The confusion matrix in Fig. 15 shows that the model has an accuracy of 99.3%. There are 5 data in the normal class which are predicted to be a stator fault class. Then, the model is tested using the testing data. The result is presented in the confusion matrix as shown in Fig. 16.

![Fig. 16](image)

**Fig. 16.** Confusion matrix testing data of single fault 3 classes on vibration signal at 749 rpm

The confusion matrix data testing in Fig. 16 shows an accuracy of 100%. It can be seen that the results of data testing under normal conditions, bearing faults and stator faults do not occur data errors. Furthermore, the results of SVM classification with other kernels are presented in Table IV.

**Table 4.** SVM Single Fault 3 Classes on Vibration Signal at 749 RPM

<table>
<thead>
<tr>
<th>Kernel</th>
<th>Feature</th>
<th>TRD (%)</th>
<th>TED (%)</th>
<th>TRD (%)</th>
<th>TED (%)</th>
<th>TRD (%)</th>
<th>TED (%)</th>
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<th>TED (%)</th>
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<td>98.9</td>
<td>99</td>
<td>98.9</td>
<td>99.4</td>
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<td>98.9</td>
<td>98.6</td>
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<tr>
<td>SVM M-Q</td>
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<td>99</td>
<td>99.4</td>
<td>99</td>
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<td>99.2</td>
<td>100</td>
<td>98.9</td>
<td>99.4</td>
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<td>100</td>
</tr>
<tr>
<td>SVM M-C</td>
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<td>99.4</td>
<td>99.3</td>
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<td>99.3</td>
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<td>99.2</td>
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<td>99.2</td>
<td>98.9</td>
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<tr>
<td>SVM M-MG</td>
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<td>98.9</td>
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</tr>
</tbody>
</table>

Table IV shows the results of the SVM classification in each kernel and the use of each number of features. In the use of 4 features, the kernel with the highest accuracy occurs in the fine Gaussian kernel with an accuracy of 99.2% for training data and 100% for testing data. In the use of 5 features, the kernel with the highest accuracy occurs in the cubic kernel with an accuracy of 99.3% for training data and 99.4% for testing data. In the use of 6 features, the kernel with the highest accuracy occurs in the cubic kernel with an accuracy of 99.3% for training data and 100% for testing data. In the use of 7 features, the kernel with the highest accuracy occurs in the cubic kernel with an accuracy of 99.3% for training data and 99.4% for testing data. In the use of 8 features, the kernel with the highest accuracy occurs in the fine gaussian kernel with an accuracy of 99.2% for training data and 100% for testing data. This shows that the SVM model is able to predict and classify data with a good level of success.

3.2.2 Speed of 1499 rpm

The results of the SVM classification for a single fault 3 classes on vibration signal at a speed of 1499 rpm are carried out for various kernel functions which can be seen in Fig. 17 as follows.

![Fig. 17](image)

**Fig. 17.** Scatter plot of single fault 3 classes on vibration signal at 1499 rpm

The scatter plot in Fig. 17 shows the SVM classification using a fine gaussian kernel. Induction motors with normal conditions are shown in orange, induction motors with bearing faults are shown in blue, and induction motors with stator faults are shown in yellow. Models that experience data errors are in the normal condition class, bearing fault and stator fault. To show the accuracy of the classification, the training data confusion matrix is shown in Fig. 18 as follows.

![Fig. 18](image)

**Fig. 18.** Confusion matrix training data of single fault 3 classes on vibration signal at 1499 rpm

The confusion matrix training data in Fig. 18 shows a model that has an accuracy of 91.1%. There are 17 data in the bearing fault class predicted as a normal class, 8 data in the bearing fault class predicted as a stator fault class, there is 1 data in the normal class predicted as a bearing fault class, 13 data in the normal class predicted as a stator fault class, there are 7 data in the stator fault class it is predicted as a bearing fault class and 18 data...
in the stator fault class is predicted as a normal class. Thus, the total misclassification that occurred was 64 data. Then, the model is tested using the testing data shown in Fig. 19 as follows.

**Fig. 19.** Confusion matrix testing data of single fault 3 classes on vibration signal at 1499 rpm

The confusion matrix testing data in Fig. 19 shows an accuracy of 90%. There are 10 data in bearing fault class predicted as normal class, 1 data in bearing fault class predicted as stator fault class, there is 1 data in normal class predicted as bearing fault class, 1 data in normal class predicted as stator fault class, 1 data in the stator fault class it is predicted as a bearing fault class and 4 data in the stator fault class is predicted as a normal class. Thus, the total misclassification that occurred was 18 data. Furthermore, the results of SVM classification with other kernels are presented in Table V as follows.

**Table 5.** SVM Single Fault 3 Classes on Vibration Signal at 1499 RPM

<table>
<thead>
<tr>
<th>Kernel</th>
<th>4 Feature</th>
<th>5 Feature</th>
<th>6 Feature</th>
<th>7 Feature</th>
<th>8 Feature</th>
</tr>
</thead>
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<tr>
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<td>TED (%)</td>
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<td>SV M-C</td>
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<td>SV M-FG</td>
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<td>SV M-CG</td>
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<td>81.7</td>
<td>81.8</td>
<td>77.2</td>
<td>80.1</td>
</tr>
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</table>

Table V shows the results of the SVM classification in each kernel and the use of each number of features. In the use of 4 features, the kernel with the highest accuracy occurs in the fine Gaussian kernel with an accuracy of 88.1% for training data and 88.3% for testing data. In the use of 5 features, the kernel with the highest accuracy occurs in the fine Gaussian kernel with an accuracy of 91.4% for training data and 86.1% for testing data. In the use of 6 features, the kernel with the highest accuracy occurs in the fine Gaussian kernel with an accuracy of 89.4% for training data and 93.3% for testing data. In the use of 7 features, the kernel with the highest accuracy occurs in the fine gaussian kernel with an accuracy of 91.1% for training data and 90% for data testing. In the use of 8 features, the kernel with the highest accuracy occurs in the fine gaussian kernel with an accuracy of 90.8% for training data and 91.1% for testing data.

Discussion on diagnosing induction motor fault by determining the optimal number of features visualized on a bar chart as seen in Fig. 20. Each data contains average accuracy information at 749 rpm speed and 1499 rpm speed.

**Fig. 20.** Average accuracy of single fault 3 classes on vibration signals

Fig. 20 shows that the average accuracy of the SVM model with various kernel functions fluctuate. The highest accuracy is achieved when using 6 features in almost all kernel except for linear kernel. The highest accuracy is 93.9 % when using fine gaussian kernel. This result is lower that obtain by Dong et.al. [16], who achieved a 99.1% accuracy through the amalgamation of VMD PCA and SVM techniques on bearing faults classification.

This results also show that in the case of induction motor faults diagnosis using the SVM model, the current signals give outstanding accuracy than the vibration signals.

### 4 Conclusions

Fault diagnosis of induction motors based on current and vibration signals using the SVM model at speeds of 749 and 1499 rpm has been carried out in this study. The variation in the utilization of the number of features aims to ascertain the optimal approach for using these features in the analysis of current and vibration signal data. The current signal produces a maximum result of 100% for each use of the number of features in each SVM kernel used. while for the vibration signal the best results are obtained by using 6 features and the fine gaussian kernel has the highest average accuracy among other kernels.

The authors thank to Sebelas Maret University for funding support to this study through through contract no. 228/UN27.22/PT.01.03/2023.

### References

1. B. L. Widjiantoro, S. Munir, and K. Indriawati, “Fault Estimation on Induction Motor Based on


