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# DETECTION OF ELECTRICAL FAULTS IN INDUCTION MOTOR FED BY INVERTER USING SUPPORT VECTOR MACHINE AND RECEIVER OPERATING CHARACTERISTIC

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**ABSTRACT**

Fault in induction motor is crucial problem in industrial processes. This paper presents the system for electrical fault detection in induction motor fed by inverter. Current spectrum with different frequency is used to fault monitoring. Faults observed includes variation of frequency, unbalance voltage, and inter turn short circuits. Through an experiment, the fault was fired and the current spectrum recorded at steady state condition. Preprocessing is performed before the identification process. It includes noise reduction using wavelet analysis and feature extraction with Principal Component Analysis (PCA). Both processes are intended to eliminate the noise, reducing the dimension of feature, and retrieve components of the optimal features for classification. Strength of identification capability using Support Vector Machine (SVM) is 83.51%. Based on the ROC (Receiver Operating Characteristic) analysis, the SVM classifier has a good enough performance. This is indicated by the sensitivity is 74.31%, specificity is 47.30% and *G-Mean is* 1.1028.

**Keywords:** *Electrical Fault Detection, Induction Motor, Principal Component Analysis (PCA), Receiver Operating Characteristic (ROC), Support Vector Machine (SVM).*

## 1. INTRODUCTION

Induction motor is widely used in industrial application. During operation, the motor may be experience with faults. If the fault is not treated then the motor may have failed that causes production activities must be stopped. So, the production process disrupts and causes energy waste.

Fault in induction motor can be either mechanical or electrical fault. In the previous study, the detected fault in induction motor are broken rotor bar [1]-[4] and bearing fault [1],[4]-[6]. Electrical fault is usually influenced by power quality that supplied by ac grid, such as variations of frequency and unbalanced voltage. Another fault is intern short circuits in stator winding [1],[7]-[10]. Some study has applied artificial intelligent method to detect the both of fault. The methods are fuzzy logic [6][10], Fast Fourier Transform (FFT) [3],[5],[6],[8], Artificial Neural Network (ANN) [7], Support Vector Machine (SVM) [4], and Kalman Filter [2].

Motor Current Spectrum Analysis (MCSA) is used as fault parameter in the motor. In industrial applications, induction machines are supplied and controlled by inverters. The effect of the inverters causes the high harmonics in the currents that were recorded due to the switching operation. Thus, it becomes more difficult and demanding to detect faults by using MCSA in this drives [3]. To get a more accurate identification, need to be done several processes to reduce the noises and eliminate features that are not desirable. Current spectrum with high noises can reduced with wavelet

transform as denoising algorithm [11]. For multidimensional data, wavelet transform will be combining with Principal Component Analysis (PCA) as denoising algorithm [12]. Observed signal usually contain many parameter feature. To increase the identification, feature extraction need to be done on original signal. Feature extraction is performed to eliminate the feature parameter that are not appropriate and reduce the dimensional of data [13]. Feature extraction methods have been

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used in previous study to improve the classification accuracy. The methods are Independent Component Analysis (ICA) [4]-[6], Kernel ICA, PCA, and Kernel PCA [6].

This study detected the electrical fault in induction motor fed by inverter. The faults are caused by variation of frequency, unbalance voltage, and inter-turn short circuits. The effect of fault and inverter in this research caused the high noise. To reduce the noises, combination wavelet and PCA are used as denoising algorithm. Feature extraction with PCA and SVM classification with ones-against-ones strategy selected to identify the fault condition.

The Performance of SVM as classifier will be determined by Receiver Operating Characteristic (ROC). In most previous studies, ROC analysis were applied on pattern recognition to diagnose a disease [14],[15]. The ROC Analysis for power system research has been tested to examine of fault identification on a radial distribution system with SVM [16]. In this paper, we use ROC analysis to determine the performance of SVM classifier for fault identification system on induction machine fed by inverter.

## 2. METHODS AND EXPERIMENT

### *2.1 The Fault Identification System*

The block diagram or lab test bench of the proposed fault identification system is shown in Fig. 1. The characteristics of the three-phase induction motor used in this experiment are listed in Table I. The Current spectrum is recorded from the motor caused driven by inverter. The faults were raised by varying the frequency of inverter, unbalance voltage, and inter turn short circuits.

TABLE I
*MOTOR CHARACTERISTIC USED IN EXPERIMENT*

| Description | Value |
|---|---|
| Power | 0.25 kW |
| Input Voltage | 380 V |
| Full Load Current | 0.82 A |
| Suply Frequency | 50 Hz |
| Number of Poles | 4 |
| Full Load Speed (rpm) | 1320 |

Fault identification consists of 4 steps that are: denoising, feature calculation, feature extraction, and classification. To determine the validity of classifier, the step is resumed by analyzing the performance of classification.

### *2.2 Denoising Signal*

Noise from current spectrum with high harmonic must be removed by filtering or denoising. Combination of wavelet transform and Principal Component Analysis (PCA) is used as de-

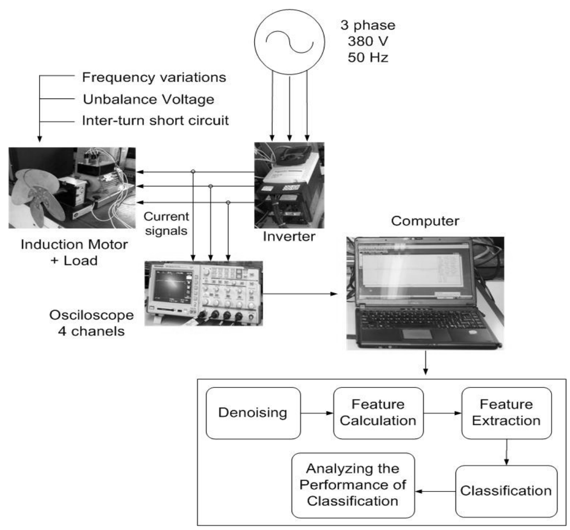


*Fig. 1. The proposed fault Identification System*

noising algorithm [12]. In general, the recorded signal is modeled as follows:

$$x(t) = f(t) + \varepsilon(t) \qquad t = 1,\dots,n \qquad (1)$$

Where $x(t)$ is observed signal, $\varepsilon(t)$ is a centered Gausian white noise of unknown var`iance and $f(t)$ is a unknown function to be recovered through the observations (Fig. 2)

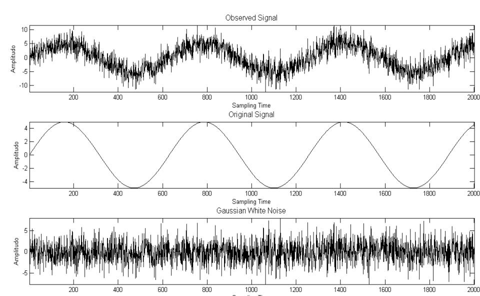


*Fig. 2. Observed Signal, Original Signal, and Gaussian White Noise*

Denoising procedure combining wavelet and PCA is applied to reduce noise in multichannel signal recording [12]. The scheme is as follows:

1) Perform the wavelet transform at level $J$ of each column of $x$ [12]-[13]
In this step, the orthogonal wavelet is decomposed to Detail signal ($D_J$) and Approximation signal ($A_J$). The orthogonal

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wavelet consists of *scaling function* ($\phi(x)$) and *wavelet function* ($\psi(x)$) (2).

$$\phi(x) = \sum_{t=0}^{J-1} a_k \phi(2x - t)$$
$$\psi(x) = \sum_{t=0}^{J-1} b_k \phi(2x - t) \quad (2)$$

Where ($a_0 - a_{J-1}$) is scaling sequence and ($b_0 - b_{J-1}$) is wavelet sequence. Scaling functions are associated with low-pass filters with coefficient $\{h(n), n \in z\}$, while wavelet functions are associated with high-pass filters with coefficient $\{g(n), n \in z\}$, (Fig 3).

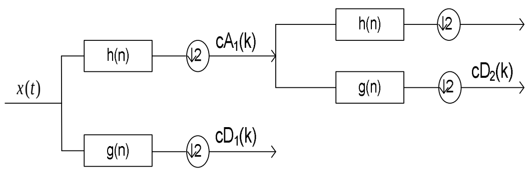


*Fig. 3. Two Level Filter Bank Decomposition Wavelet*

In this way, the decomposition coefficient can be described as (3):

$$[x(t)] \leftrightarrow [cA_1, cD_1] \leftrightarrow [cA_3, cD_3, cD_2, cD_1] \leftrightarrow .... \quad (3)$$

2) For $1 \le j \le J$, perform the PCA of the matrix $cD_j$ and select an appropriate number $p_j$ of useful principal component or suppress the detail $cD_j$;
3) Similarly, perform the PCA from the matrix $cA_J$ and select $p_{J+1}$ principal component;
4) From the simplified detail and approximation matrices reconstruct a new matrix $\breve{x}$ containing the main features of the original matrix *x*, by inverting the wavelet transform;
5) Finally perform the PCA of the matrix $\breve{x}$.

## 2.3 Feature Calculation and Feature Extraction

After denoising, feature parameters are calculated based on time domain and frequency domain. There are 25 feature parameters of each phase (phase R, S, and T). We have 10 conditions and each one has 20 measurements, so the total obtained 200 data calculated. The value of features parameter calculated based statistical value of time domain and frequency domain, such as mean, RMS, variance, peaks, moment, entropy, crest factor, Total Harmonic Distortion, etc.

We used PCA as feature extraction algorithm [17]-[18]. PCA will reduce the dimension of parameter but not eliminate the information about the signal. The result is a parameter called Principal Component. The procedure involves eigenvalue and eigenvector as follows:

1. Given a set of *n* dimension input vector and each of which is of *m* dimension.

$$x(t) = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (4)$$

2. Subtracting the value of each cell $x_{ij}$ with an overall mean $\mu_j$

$$u_j = \frac{1}{m}\sum_{i=1}^{m} x_{ij} \quad (5)$$

$$\phi_{ij} = x_{ij} - \mu_j \quad (6)$$

3. Calculate the matrix covariance *C*

$$C = (x_{ij} - \mu_j)(x_{ij} - \mu_j)^T \quad (7)$$

4. Getting the eigenvalue $\lambda$ and eigenvector *u* of matrix covariance *C*

$$\lambda_i u_i = C u_i \quad (8)$$

Where $\lambda_i$ is eigenvalue of *C*, $u_i$ is the corresponding eigenvector.

5. Based on the estimated $u_i$, the components of $s_t$ are the orthogonal transformations of $x_t$

$$s_t(i) = u_i^T x_t \quad (9)$$

$s_t(i)$ are called principal components. Dimensional reduction of parameters is executed in (9). By using a specific threshold of the eigenvector, $u_i$, the dimension of the final data can be determined.

## 2.4 Classification

In this study, Support Vector Machine (SVM) is used to identify fault of induction motor. All the measured data are classified into 10 types of fault. From each type, it is selected 30% measurement as training and 70% as testing data.

SVM maps the input vectors *x* into a high-dimensional features space *Z* through some nonlinear mapping [19]. In this space, an optimal separating hyperplane is constructed (Fig. 4).

The learning machines construct the decision functions that are nonlinear in the input space,

$$f(x) = sign\left( \sum_{\text{supportvectors}} y_i \alpha_i K(x_i, x) - b \right) \quad (10)$$

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To find the coefficients $\alpha_i$ in the separable case (analogously in the non-separable case) it is sufficient to find the maximum of the functional.

$$W(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i,j}^{n} \alpha_i \alpha_j y_i y_j K(x_i, x_j) \quad (11)$$

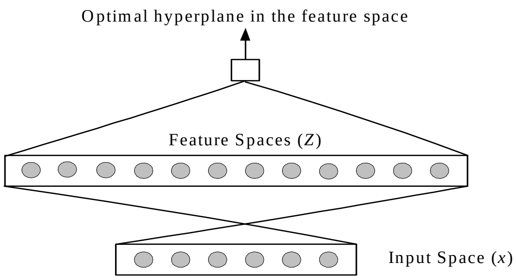


*Fig. 4 The SV Machine maps the input space into a high-dimensional feature and then constructs an Optimal hyperplane in the feature space*

Subject to the constraints

$$\sum_{i=1}^{n} \alpha_i y_i = 0 \qquad \alpha_i \geq 0, \qquad i = 1,2,\ldots,n \qquad (12)$$

*$K(x_i,x)$* is the Kernel function in input space that equivalent with inner product in feature space. $K$ is a symmetric positive definite function which satisfies Mercer's condition.

$$K(x_i, x) = \sum_{k=1}^{\infty} a_k \psi_k(x_i)\psi_k(x) \qquad a_k \rangle 0 \qquad (13)$$

It is necessary and sufficient that the condition

$$\iint K(x_i, x) g(x_i) g(x) dx_i dx \rangle 0$$

Be valid for all g ≠ 0 for which

$$\int g^2(x_i) dx_i \langle \infty$$

Examples of such kernels are given in Table II.

TABLE II
*EXAMPLE OF KERNEL FUNCTIONS*

| No | Kernel Type | Functions |
|---|---|---|
| 1 | Polynomial | $K(x_i, x) = \langle x_i, x \rangle^d$ |
| 2 | Gausian Radial Basis Function | $K(x_i, x) = \exp\left(-\frac{\lVert x_i - x \rVert^2}{2\sigma^2}\right)$ |
| 3 | Exponential Radial Basis Function | $K(x_i, x) = \exp\left(-\frac{\lVert x_i - x \rVert}{2\sigma^2}\right)$ |
| 4 | Fourier Series | $K(x_i, x) = \frac{\sin\left(N + \frac{1}{2}\right)(x_i - x)}{\sin\left(\frac{1}{2}(x_i - x)\right)}$ |

The optimal hyperplane separated without error and the distance between the closest vector to the hyperplane is maximal (Fig. 5). Suppose the training data

$$(x_i, y_i), \ldots, (x_l, y_l), \quad x \in R^n, \quad y \in \{+1, -1\}$$

Can be separated by a hyperplane :

$$(w, x) + b = 0 \qquad (14)$$

where, $w$ and $b$ shall be derived in such a way that unseen data can be classified correctly. To describe the separating hyperplane, the following canonical form can be use:

$$(w.x_i) + b \geq \ \ 1 \qquad if \ \ y = +1,$$

$$(w.x_i) + b \leq -1 \qquad if \ \ y_i = -1.$$

In the following we use a compact notation for these inequalities:

$$y_i\left[(w.x_i) + b \geq 1, \qquad i = 1,\ldots,n\right] \qquad (15)$$

It is easy to check that the optimal hyperplane is the one that satisfies the condition (15) and minimizes (Fig. 5).

$$\Phi(w) = \lVert w \rVert^2 \qquad (16)$$

(The minimization is taken with respect to both vector $w$ and scalar $b$)

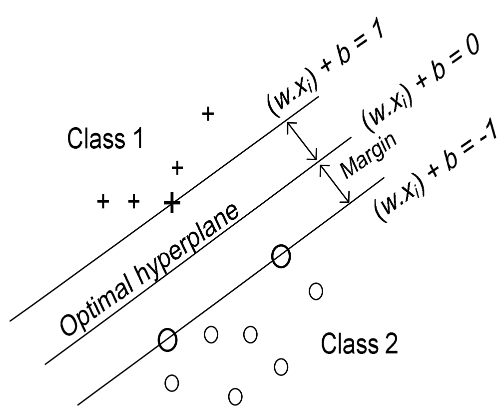


*Fig. 5. The Optimal separating hyperplane is the one that separates the data with maximal margin.*

*2.5 Analysis the Performance of Classification*

Classification performance can be analyzed by graph Receiver Operating Characteristic (ROC). ROC graph is a technique to visualize, organize, and choose the type of classification based on its performance [20].

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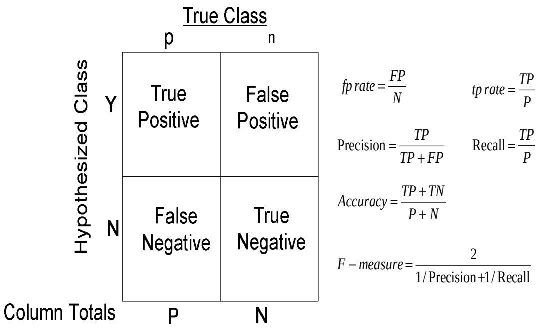


*Fig. 6. Confusion matrix and common performance matrix calculated from it*

Classification performance is determined by confusion matrix. In binary classification, the outcomes are labeled either as positive (*p*) or negative (*n*) class. There are four possible outcomes from a binary classifier. They are *true positive*, *false negative*, *true negative*, and *false positive* (Fig 6). For example, to determine weather a signal has a certain fault. A *true positive* in this case occurs when the signal test is positive (fault) and actually it is positive. A *false positive*, on the other hand, occurs when the test is positive and actually it is negative, similarly for *true negative* and *false negative*.

Fig 6 shows a confusion matrix and equations of several common that can be calculated from it. The numbers along the major diagonal represent the correct decisions made, while the numbers in this diagonal represent the errors —the confusion — between the various classes.

Performance of a classifier can be caused by the imbalance data set. Evaluation the imbalanced classification based on confusion matrix in Fig. 6. There are two kinds of metrics to deal with class imbalanced [21].

The first metrics to obtain an optimal balanced classification ability are *sensitivity* (17), *specificity* (18) and *G-Mean* (19). There are usually adopted to separately monitor the classification performance on two classes. *G-Mean* is the geometric mean of sensitivity and specificity (19).

$$sensitivity = \frac{True\ Positive}{(True\ Positive + Fals\ Negative)} \quad (17)$$

$$specificity = \frac{True\ Negative}{(True\ Negative + Fals\ Positive)} \quad (18)$$

$$G - Mean = \sqrt{sensitivity + specificity} \quad (19)$$

The second metrics are *precision*, *recall*, and *F-Measure* (Fig. 6). Notice that recall is the same as sensitivity. F-Measure is used to integrate precision and recall into a single metric.

## 3. RESULT AND ANALYSIS

Lab experiments have been done and result in recorded signal of 10 fault conditions with 20 measurements every condition. To identify the fault, it is conducted steps as mentioned in previous section that are denoising process, feature calculation, feature extraction, and classification.

### *3.1 Denoising Result*

Current signal are recorded in this study and have a very high noise. This noise must be removed to avoid bias. Fig. 7 shows example 4 types of three phase current signals that have been filtered using combination of wavelet and PCA. The current signals include normal (no-fault, inter-turn short circuit, and 5% and 10% unbalanced voltage condition.

As seen in Fig.7, combination of wavelet and PCA eliminate the noises. To distinguish the current signal due to unbalance voltage 5% and 10% is difficult, because the spectrum seems very similar. It needs a tool to quickly and accurately recognize faults using the step as describe in previous section.

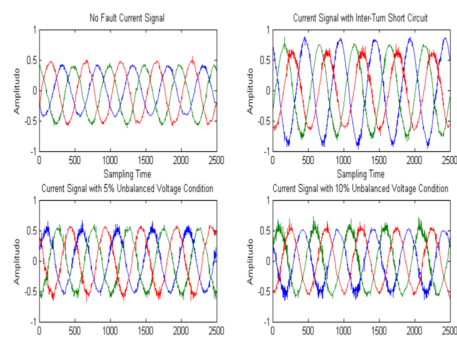


*Fig. 7. Denoising Current Signal with Combination of Wavelet and PCA.*

### *3.2 Feature Calculation and Feature Extraction Result*

Figure 8 shows the eigenvalue of 25 feature parameters. Only 14 of 25 parameters are selected as principal components to be identified. Selection is based on the high enough eigenvalue. The others are discarded, due to too small.

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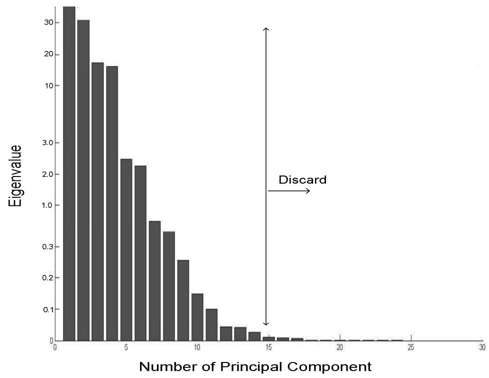


*Fig 8. Eigenvalue of Covariance matrix for Feature Selection*

In order to show the scatter diagram of faults belongs to each principal component, the 3 biggest eigenvalues of principal components is selected. Fig. 9 shows the scatter diagram of extracted 3 principal component using PCA. As can be seen, the data tends to distribute in a group based on the fault types.

*3.3 Identification Result and It's Performance*

Fault identification of 14 principal components using SVM method is presented in Table III. The normal condition of 50 Hz frequency can be identified perfectly, presenting 100% of the strength of identification index. The average in 83.51%.

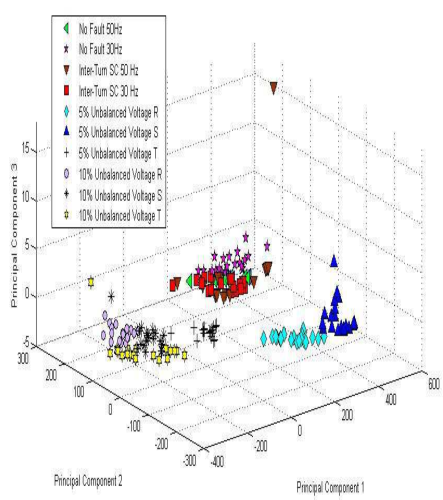


*Fig. 9 Scatter Diagram for 3 Largest Principal Component*

TABLE III

*IDENTIFICATION RESULT USING SVM*

| Fault Condition | Frequency (Hz) | Strength of Identification (%) |
|---|---|---|
| No Fault | 50 | 100 |
| No Fault | 30 | 93.85 |
| Inter-Turn Short Circuits | 50 | 72.31 |
| Inter-Turn Short Circuits | 30 | 84.62 |
| Average 5% Unbalance Voltage | 50 | 81.28 |
| Average 10% Unbalance Voltage | 50 | 68.97 |
| **Average** | | **83.51** |

The performance of SVM classifier is based on ROC analysis, determined in Fig. 10 and Table IV. As seen in Fig. 10, there are 1561 Positive sample (P) and 389 Negative samples (N). There are 1160 samples of 1561 demonstrating a correct identification (True Positive), while 401 samples are False Negative (FN). FN means that the system has no faults, but it was recognized having fault. On the other hand, FP is a resent of SVM identification that system has faults, but it was recognized normal condition.

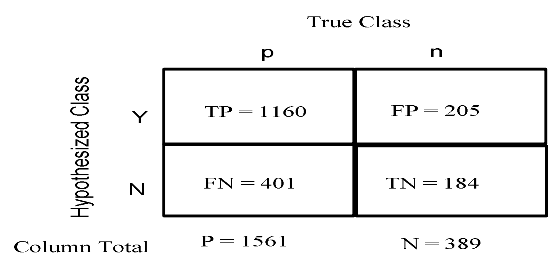


*Fig. 10 Confusion Matrix of Fault Identification*

Table IV shows *Sensitivity* or *TP rate* as 0.7431. This indicates the system ability to recognize true signal as 74.31%. However, the ability of system to recognize a wrong signal as *specificity* is 47.30%. It is calculated from the ratio of TN and total negative samples. Other parameter is found as precision, which is 84.98% calculating from Fig. 6.

TABLE IV

*PERFORMANCE OF SVM CLASSIFIER BY ROC*

| No | Variable | Prob. Value |
|---|---|---|
| 1 | Sensitivity = TP rate | 0.7481 |
| 2 | Specificity | 0.4730 |
| 3 | Precision | 0.8498 |
| 4 | G-mean | 1.1028 |

The Geometric mean (*G-Mean*) is presented as 1.028. It represents the balanced result between

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sensitivity and specificity. G-mean is evenly balanced when the value is 1.0. A better G-Mean is obtained if the value is greater than 1.0.

## 4. CONCLUSION

Electricity faults in induction motor in this study are identified by SVM based on current signal. The current signals are very noisy since they are generated from a small rate of equipment. Before the process of identification, It is necessary to pre process the recorded signals for accurate improvement. This includes, denoising signal with combination of wavelet and PCA, feature calculation based on time and frequency domain, and feature extraction using PCA. The study present was 4 principal components of 25 feature parameters based on its eigenvalue. The faults of induction motor are identified by SVM with strength of identification index average in 83.51%. Based on ROC analysis, the ability of system recognizes the true signal is 74.31% (sensitivity) and the wrong signal is 47.30% (specificity). G-Mean is balanced because the value is greater than 1.0.

In the future, current signals from bigger rate of equipment will be observed with more types of fault. To improve the performance of SVM considers improving the feature extraction and feature selection algorithm.

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