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Multi-Sensor Fault Diagnosis of Induction Motors Using Random Forests and Support Vector Machine

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Abstract -- This paper presents a fault diagnosis scheme for induction machines (IMs) using Support Vector Machine (SVM) and Random Forests (RFs). First, a number of time-domain and frequency-domain features are extracted from vibration and current signals in different operating conditions of IM. Then, these features are combined and considered as the input of SVM-based classification model. To avoid overfitting, RF is utilized to determine the most dominant features contributing to accurate classification. It is proved that the proposed method is capable of achieving highly accurate fault diagnosis results for broken rotor bar and eccentricity faults and it can appropriately handle the high dimensionality of the combined data.

Index Terms -- Fault diagnosis, induction motor, machine learning, multiple signal classification, support vector machine.

I. INTRODUCTION

Induction machines (IMs) are considered as vital electromechanical components of industry infrastructure. Therefore, their highly reliable and safe operation is really demanded in the industry. Various faulty conditions can occur in motor components during operations due to impacts, fatigue, insufficient lubrication, aging, and so on [1]. Operational faults regarding IMs are categorized into two main groups, electrical and mechanical faults. Mechanical faults consist of problems with bearings, static and dynamic eccentricity, and wear coupling misalignment, while electrical faults contain problems related to stator and rotor windings, rotor bar breakage, and faulty connections [2]. The appropriate condition monitoring and timely diagnostics of incipient faults prevents time-consuming maintenances in which the motors are offline for long periods. In order to prevent performance reduction and malfunctions, a large number of studies and efforts in condition monitoring and fault detection and diagnosis in the dynamic modeling of machine components have been carried out. The conventional time-domain fault diagnosis approaches relying on human intervention have some disadvantages due to the fact that the diagnosticians

encounter a plethora of problems in case of dealing with multiple features from various signal processing methods especially when the signals are contaminated with noise [3].

A number of signal processing approaches have been developed to enhance motor fault detection, using vibration analysis [4] and motor current signature analysis (MCSA) [5]. Although many fault diagnosis indexes are proposed to present deterministic models that can classify different faulty cases, these deterministic models are not effective regarding the uncertainties that normally exist in real-world cases [6]. This is owing to various operating conditions of machines such as different inverter feedings and motor load levels, noise and disturbance from other signal sources, dynamics related to the nonlinearity of the system, etc. On the other hand, data-driven methods are better options for dealing with such cases, and therefore attracted the attention of the researchers.

Recently, machine learning has become a popular technique to be employed in data-driven fault diagnosis. Both supervised and unsupervised learning have demonstrated to be effective in condition monitoring [7]. Supervised learning systems, such as support vector machine (SVM) were firstly applied to fault diagnosis in the late 1990s [8]. Artificial neural networks (ANNs) [9], Fuzzy logic [10], and K-Nearest Neighbor (KNN) [11] are also employed in condition monitoring of engineering applications. The unsupervised learning methods such as K-means clustering [12] and Principal Component Analysis (PCA) [13] are other potential applications of machine learning which have been reported in the literature. Among different machine learning methods, SVM has been recently considered as one of the most popular ones being used in many research works to train the classifier for fault diagnosis [14].

Both vibration analysis and MCSA are considered as non-invasive methods in fault diagnosis of rotary machines and many commercialized systems containing vibration and current sensors are employed in industry. Comparison of these two approaches shows that the accuracy of IM fault detection depends on the fault diagnosis method which has been selected. It is reported that MCSA techniques are more effective in detection of electrical faults, while vibration analysis techniques are more precise in dealing with mechanical faults [15]. This is because each type of sensor signal contains specific information related to certain working condition. Therefore, fusing these sensors and monitoring them together can be an efficient method to

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Fig. 1. The procedure of fault detection and classification

enhance the performance of fault diagnosis and enable multi-fault classification simultaneously under complex conditions [16].

The bearing faults are the most probable faults in IMs. Therefore, the majority of research works in the literature have been dedicated to addressing these types of faults [17]. However, the broken rotor bar (BRB) and eccentricity faults are also of great importance since they both significantly affect the mechanical, electrical, and magnetic quantities of motor that result in highly undesirable operation of IM. Moreover, it is critical to detect these faults at their incipient levels due to their inherently degenerative nature [18].

This paper presents a data-driven diagnosis method for BRB and eccentricity faults in IMs using both current and vibration signals based on SVM method. The simultaneous presence of these faults is also taken into account. A major concern that is addressed in this paper is the robustness of the fault diagnosis method in case of lack of available data for some loading conditions. The SVM-based classifier is trained by using three-phase current sensors' data and eighteen vibration sensors located in different positions of the motor. After extracting time-domain and frequency-domain features, these features have been combined and utilized in the training process. It should be noted that the increased number of features after feature concatenation may lead to overfitting due to the high dimensionality of the input data and decrease the accuracy of fault detection. In order to address this problem, we have used the ensemble learning model, Random Forests (RF) as the feature selection method and combined it with the SVM model. Using RF prevents the classifier from overfitting by removing the undesirable and irrelevant features that don't contribute to accurate prediction of the model. The procedure of the developed fault detection and classification scheme of this paper is illustrated in Fig. 1.

Fig. 2. SVM linear classification of two classes, the blue dots are negative labels and the green ones are positive.

Fig. 3. Soft Margin SVM classifier

II. SUPPORT VECTOR MACHINE (SVM)

Support Vector Machine (SVM) is a supervised machine learning technique introduced by Vapnik and his co-workers in the mid of 1990s [19]. The main idea behind SVM is to draw a hyperplane in n -dimensional space such that it maximizes the margin between classification groups. The support vector machine is generally designed for two class problems. This is a binary classification, where one class is the positive class and the other one is negative. This method separates two different classes of data by choosing suitable boundary line or hyperplane.

Let us assume we have a training dataset for binary classification problem: $(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \dots, (\mathbf{x}_k, y_k)$ with $\mathbf{x}_i \in R^n$ and k being the total number of training samples. The output labels consist of positive ($y_i = +1$) and negative ($y_i = -1$) labels. As shown in Fig. 2, there are many possible ways to separate the two classes. However, to select the optimal one, the line must have the maximal distance (margin) between the two classes' adjacent points. These points are called support vectors. The optimal hyperplane is depicted in Fig. 2 by the red color line. The primary target of SVM is to maximize the margin and place the boundary line between it. The following equation expresses the boundary line D_0 , which attempts to classify the two classes:

$$f(\mathbf{x}_i) = (\mathbf{w}^T \mathbf{x}_i + b), \quad (1)$$

where $\mathbf{x}_i$ represents the input vector, $\mathbf{w} \in R^n$ is a weight vector, and b is a scalar threshold. If the sign of $f(\mathbf{x}_i)$ is positive, the observation $\mathbf{x}_i$ will have positive label ($y_i = +1$) and vice versa. The distance from the observation $\mathbf{x}_i$ to the separator boundary can be defined as

$$r = \frac{y_i(\mathbf{w}^T \mathbf{x}_i + b)}{\|\mathbf{w}\|}. \quad (2)$$

Now, by considering the constraint $y_i(\mathbf{w}^T \mathbf{x}_i + b) \geq 1$, for each observation i , we can maximize the distance (margin) by minimizing $\|\mathbf{w}\|$.

So far we implicitly assumed our dataset is linearly separable. However, most of the real datasets are noisy and cannot be separated without error. To handle this case, soft margin SVM is developed with relaxed constraints in which certain number of data points are allowed to lie beyond the boundary [19]. This can be done by introducing slack variables ξ_i to the constraints. It can be observed from Fig. 3 that when $\xi_i = 0$, the observation i is classified correctly and it is located on the right side of the hyperplane and outside of the margin. When $0 < \xi_i < 1$, the observation i is classified correctly but is within the margin and when $\xi_i > 1$, the observation i is misclassified and it is on the wrong side of the hyperplane. The soft margin SVM optimization problem can be formulated as follows:

$$\begin{aligned} & \text{minimize} \quad \frac{1}{2} \|\mathbf{w}\|^2 + C \sum_{i=1}^N \xi_i \\ & \text{subject to} \quad y_i(\mathbf{w}^T \mathbf{x}_i + b) \geq 1 - \xi_i \quad \xi_i \geq 0, \end{aligned} \quad (3)$$

where C is called the slack penalty that controls maximizing the margin and minimizing the training error. The above optimization can be easily solved by the methods of Lagrangian multipliers and dual decomposition [19].

So far the linear SVM model is introduced. In many cases including the application of fault diagnosis of rotary machines, even if the hyperplane is determined to be optimal, the training data cannot be appropriately classified by linear SVM due to its high nonlinearity. To deal with this type of problems, the original space can be transferred to a high dimensional space ($\mathbf{x} \rightarrow \boldsymbol{\phi}(\mathbf{x})$), where it can be classified by linear classification method [20]. However, computing $\boldsymbol{\phi}(\mathbf{x})$ is very complicated and time-consuming. To overcome this, the kernel function is introduced as $k(\mathbf{x}, \mathbf{x}_i) = \boldsymbol{\phi}(\mathbf{x}) \cdot \boldsymbol{\phi}(\mathbf{x}_i)$. A kernel is a similarity measure which takes two inputs and outputs their similarity. The linear decision boundary in high dimensional space can be given by the following equation where the input vector $\mathbf{x}$ is transferred to high dimensional space $\boldsymbol{\phi}(\mathbf{x})$ and α_i is the Lagrangian multiplier:

$$f(\mathbf{x}) = \sum_{i=1}^N \{\alpha_i y_i k(\mathbf{x}, \mathbf{x}_i)\} + b. \quad (4)$$

Among different kernel functions that can be used, the most common one is the radial basis function (RBF) or Gaussian kernel which can be expressed as follows:

$$k(\mathbf{x}, \mathbf{x}_i) = e^{-\frac{\|\mathbf{x} - \mathbf{x}_i\|^2}{2\sigma^2}}, \quad (5)$$

where σ is a free parameter controlling the smoothness of the Gaussian kernel.

(a)

Fig. 4. (a) Measurement setup, (b) Schematic of the measurement setup, (c) Location of the five accelerometers

TABLE I
IM SPECIFICATIONS

Parameter	Symbol	Value
Connection	Y-Δ	Star
Rotor Slots	N_r	40 (non-skewed)
Stator Slots	N_s	48 (non-skewed)
Number of poles	P	4
Rated power	P_r	18 kW (50 Hz)
Rated slip	S	0.0667
Terminal voltage	V	333V (50 Hz)

III. EXPERIMENTAL STUDIES AND DATA ACQUISITION

The input data of the SVM-based classifier is obtained from the measurement setup depicted in Fig. 4. The setup includes an IM under study with the parameters given in Table I. The investigated IM is fed from the main grid and is connected to a similar IM, which operates in generator mode and acts as the loading machine. To enable different loading levels, the loading IM is connected to a frequency converter. The Dewetron data acquisition system is used to record the three-phase current signals. For obtaining the vibration signals, five Kistler 8763B050AB triaxial accelerometers are employed; they are located on the circumference of the tested IM according to Fig. 4c. A Digital Signal Recorder (DSR) is used to record all the measured signals with the sampling rate of 10000 samples per second and they are stored in the computer. The duration of measurement is 23.2 seconds.

TABLE II
TIME-DOMAIN AND FREQUENCY-DOMAIN FEATURES

Time-domain features		Frequency-domain features	
$TD_1 = T_{max} = \max(x_i)$	$TD_{11} = T_{ave} = \frac{1}{N} \sum_{i=1}^N x_i $	$FD_1 = \frac{\sum_{k=1}^K s(k)}{K}$	$FD_7 = \sqrt{\frac{\sum_{k=1}^K f_k^2 s(k)}{\sum_{k=1}^K s(k)}}$
$TD_2 = T_{rms} = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i)^2}$	$TD_{12} = T_{pf} = \frac{T_{max}}{T_m}$	$FD_2 = \frac{\sum_{k=1}^K (s(k) - FD_1)^2}{K-1}$	$FD_8 = \sqrt{\frac{\sum_{k=1}^K f_k^4 s(k)}{\sum_{k=1}^K f_k^2 s(k)}}$
$TD_3 = T_{kurt} = \frac{1}{N-1} \sum_{i=1}^N \frac{(x_i - \mu)^4}{\sigma^4}$	$TD_{13} = T_{sf} = \frac{T_{rms}}{T_{ave}}$	$FD_3 = \frac{\sum_{k=1}^K (s(k) - FD_1)^3}{K(\sqrt{FD_2})^3}$	$FD_9 = \frac{\sum_{k=1}^K f_k^2 s(k)}{\sqrt{\sum_{k=1}^K s(k) \sum_{k=1}^K f_k^4 s(k)}}$
$TD_4 = T_{skew} = \frac{1}{N} \sum_{i=1}^N \frac{(x_i - \mu)^3}{\sigma^3}$	$TD_{14} = T_{cf} = \frac{T_{peak}}{T_{rms}}$	$FD_4 = \frac{\sum_{k=1}^K (s(k) - FD_1)^4}{KFD_2^2}$	$FD_{10} = \frac{FD_6}{FD_5}$
$TD_5 = T_{min} = \min(x_i)$	$TD_{15} = T_{if} = \frac{T_{peak}}{T_{ave}}$	$FD_5 = \frac{\sum_{k=1}^K f_k s(k)}{s(k)}$	$FD_{11} = \frac{\sum_{k=1}^K (f_k - FD_5)^2 s(k)}{KFD_6^2}$
$TD_6 = T_{var} = \frac{1}{N-1} \sum_{i=1}^N (x_i - T_m)^2$	$TD_{16} = T_{sra} = \left(\frac{1}{N} \sum_{i=1}^N x_i \right)^2$	$FD_6 = \frac{\sum_{k=1}^K (f_k - FD_5)^2 s(k)}{K}$	$FD_{12} = \frac{\sum_{k=1}^K (f_k - FD_5)^4 s(k)}{KFD_6^4}$
$TD_7 = T_{p-p} = T_{DF6} - T_{min}$	$TD_{17} = T_{mf} = \frac{T_{max}}{T_{sra}}$		
$TD_8 = T_{mad} = \frac{1}{N} \sum_{i=1}^N x_i - \bar{x} $	$TD_{18} = T_{as} = \frac{1}{N} \sum_{i=1}^N x_i^2$	- x_i is the time-domain signal data point and N is the total number of data points.	
$TD_9 = T_{peak2rms} = \frac{ x _{\infty}}{\sqrt{\frac{1}{N} \sum_{i=1}^N x_i ^2}}$	$TD_{19} = T_{rss} = \sqrt{\sum_{i=1}^N x_i ^2}$	- f_k is the frequency value of the kth spectrum line.	
$TD_{10} = T_{peak} = \max x_i $	$TD_{20} = T_{clf} = \frac{T_{peak}}{T_{sra}}$	- $S(k)$ is the kth spectrum.	
		- K is the number of spectrum lines.	

Seven different conditions of the motor are considered in this research work including the healthy case and six faulty cases. The signals are measured under the following cases: healthy, eccentric rotor with 28.5% dynamic eccentricity, one BRB, two consecutive BRBs, three BRBs, simultaneous fault of two BRBs and dynamic eccentricity, and two non-consecutive BRBs. The six faulty cases are categorized from F1 to F6. Three different loading levels for IM are considered including full-load, half-load, and no-load operations in which the phase current is 40A, 30A, and 18A, respectively. Therefore, the total number of obtained datasets is 21. For each dataset, there are 290 samples and each sample contains 800 data points.

IV. FEATURE EXTRACTION AND SELECTION

A. Feature Extraction

The feature extraction is the process of extracting the essential aspects of measured data without distorting it. This method is among the critical aspects of the classification process. It helps to produce relevant features and makes the classification process faster and smoother. In this research work, 20 ordinary time-domain features and 12 frequency-domain features have been selected from each of the vibration/current signals which are given in Table II. The main purpose of this study is to increase the diagnostic information of the features in spite of choosing simple and straightforward features. Therefore, all the features obtained from different sensors are concatenated leading to a combined list of 576 features for each sample of our datasets.

B. Random Forest Feature Selection

In the previous step, a lot of possible features were extracted from 18 vibration and current signals and then, we combined these features to increase the diagnostic accuracy of our model as a result of enhanced complementary information. However, it is not guaranteed that all the 576 features contain useful information for our classification

purpose and a lot of features may be correlated which is not desirable. Moreover, the increased number of features correspondingly increases the training time due to the high dimensionality of the feature set. Feature selection is an effective method that can be used to select the most discriminative features and enhance the performance of the data-driven diagnostic system in terms of either accuracy or computational time [21]. The ensemble learning model, RF has been previously utilized in condition monitoring of IMs [22]. In this paper, RF is used for performing feature selection. RF can be considered as an improved version of bagged decision trees or bootstrap aggregation [23]. Although decision trees provide ease of interpretation and inference compared with other machine learning models, they suffer from high variance and overfitting. This problem can be handled in bagging method by taking K repeated random samples with replacement from the training data set and then fitting a decision tree to each sampled data set. These decision trees are called the base estimators. It should be noted that the size of each random sampled data set is similar to the size of the original training data set. When the training process for all K bootstrapped data sets is finished, the final classification model can be built by using majority voting from the K decision trees. A potential disadvantage of bagged trees is the existence of high correlation between the K base estimators which decreases the prediction accuracy. This correlation is due to the effect of dominant features which are used in most of the K base estimators each time a split in a tree is established. To address this issue, the RF method uses only a random subset of features as split candidates each time a split is built in its base estimators. By doing this, the base estimators will be decorrelated significantly and their complementarity will increase, improving the accuracy of the ensemble model [23]. After implementing the RF method on our data set, the most informative features are recognized based on their prediction ability and can be used to train the SVM-based classification

Fig. 5. The top 50 features' importance scores after implementing RF

scheme. Fig. 5 shows the top 50 features ranked based on their importance score among the 576 features. The importance score is calculated based on the value each feature reduces the impurity measure in a decision tree. In RF method, these reduction values are averaged over all the base estimators and then, the feature importance scores are obtained. It can be understood from Fig. 5 that the features obtained from vibration sensors are more effective than current sensors' features. Moreover, the features from z-direction vibration signals especially the fifth vibration sensor have substantial importance scores. To increase the generalization ability of the developed classifier and to avoid the curse of dimensionality, we have selected the top 35 features in Fig. 5 which is 6 percent of the total features.

V. RESULTS AND DISCUSSION

To validate the performance of the proposed fault diagnosis scheme, the features selected by RF method, are now utilized to train the SVM classifier. The RBF kernel function is selected for classification. To enable the multiclass classification problem, one-against-all method is employed [14]. The two parameters C and σ in SVM formulation are considered as hyper-parameters. Finding optimal hyper-parameters is a challenging task. To simplify this process, the 10-fold cross-validation (CV) and grid-search methods are used. Different pairs of (C, σ) values are tried and tested for choosing the best setting having the highest CV accuracy. At the first scenario of the implementation, the entire dataset containing all loading levels i.e., full-load, half-load, and no-load, is initially split into 70% of a training set and 30% of the test set, and the training set was used to train the SVM model. The 10-fold CV accuracy for the SVM model is 100%. Fig. 6a depicts the confusion matrix for testing data set. It can be seen from Fig. 6a that in case of using all loading levels in the training process and implementing feature concatenation, the fault diagnosis system works properly. It can discriminate between different severities of BRB fault and also the simultaneous fault of BRB and eccentricity (F5). The overall accuracy for all seven faulty and healthy conditions is 99.11% which is promising.

Another major concern of this study is to verify the effectiveness of the developed classification method when there is a lack of sufficient data for training. In many practical and industrial applications of IMs, it is difficult to provide training data for all operating conditions. Therefore, it is important to develop a robust fault diagnosis system being able to handle the classification when the data is not available for all loading levels. Fig. 6b shows the test confusion matrix for the second scenario in which the full-load and no-load data are used for training and the half-load data is used for testing. It can be seen that except for the fault F2 (one BRB) where the accuracy is 89.3%, the SVM-based model can classify all the cases with an acceptable performance. The overall accuracy for this scenario is 97.86% showing the robustness of the proposed method. The high efficiency of the developed fault diagnosis technique can be attributed to different factors including using combined features from multi-sensor data, well-performed feature selection by the RF model, and fine-tuning of the SVM model. The comparisons of prediction accuracy between multi-sensor and single-sensor strategies are illustrated in Figs 7 and 8 for scenarios 1 and 2, respectively. Among the 15 vibration signals, the performance of the fifth vibration sensor in z-direction was the best and therefore, it is selected in both figures to show the results of using single-sensor vibration-based fault diagnosis. According to both figures, using multi-sensor data is preferable compared with single-sensor data. This is due to the fact that different sensors contain complementary information and each sensor has its own contribution to the fault diagnosis. It can be understood from both figures that the contribution of vibration sensors is significantly higher than current sensors. By adding the current sensors' data to the vibration signals, the overall accuracy of fault diagnosis for first and second scenarios are increased for only 0.41% and 1.14%, respectively. Fig. 8 shows that for most faulty cases in scenario 2, if a single sensor is used, the fault diagnosis system is only capable of identifying a few faults and its accuracy for the rest of the faults is too low. Hence, the difference between the accuracy of multi-sensor and single-sensor strategies in the second scenario is higher than the

Fig. 6. Confusion matrix for multi-sensor SVM-based classifier. (a) All the loading levels are used in training. (b) Full-load and no-load data is used for training and half-load is used as test data.

Fig. 7. Prediction performance of the classifier when all the loading levels are used in the training.

Fig. 8. Prediction performance of the classifier when full-load and no-load data is used for training and half-load is used as test data.

first scenario. Moreover, the effect of increased complementarity as a result of locating five accelerometers at different positions of the motor can be easily seen in Fig. 8 where the overall prediction accuracy of using all vibration signals with concatenated features is 96.6% while for the fifth vibration sensor in z-direction, the value of accuracy is only 86.12%.

VI. CONCLUSION

In this work, a data-driven fault detection and diagnosis method based on multi-class SVM is presented for the IM. Both current and vibration sensors are used for training the classifier and in order to identify the most discriminative features, RF is used for feature selection. The performance of the proposed method has been validated by two experimental data sets. In the first data set, all the loading levels have been participated in both training and testing process while in the second one, the test data has been chosen to have a different loading level than the training data. The experimental results indicate the effectiveness of the proposed method. Future works include focusing on the state of the art sensor fusion techniques and exploring their effect on the performance of the fault diagnosis system.

REFERENCES

- [1] X. Liang, M. Z. Ali, and H. Zhang, "Induction Motors Fault Diagnosis Using Finite Element Method: A Review," *IEEE Trans. Ind. Appl.*, vol. 9994, no. c, pp. 1–1, 2019.
- [2] A. M. Bazzi and P. T. Krein, "Review of Methods for Real-Time Loss Minimization in Induction Machines," *IEEE Trans. Ind. Appl.*, vol. 46, no. 6, pp. 2319–2328, Nov. 2010.
- [3] S. Chen, X. Dong, Y. Xiong, Z. Peng, and W. Zhang, "Nonstationary Signal Denoising Using an Envelope-Tracking Filter," *IEEE/ASME Trans. Mechatronics*, vol. 23, no. 4, pp. 2004–2015, 2018.
- [4] V. Climente-Alarcon, J. Antonino-Daviu, F. Vedral-Santos, and R. Puche-Panadero, "Vibration transient detection of broken bars by PSH sidebands," in *2012 XXth International Conference on Electrical Machines*, 2012, pp. 2517–2521.
- [5] B. Come, B. Vervisch, S. Derammelaere, J. Knockaert, and J. Desmet, "The reflection of evolving bearing faults in the stator current's extended park vector approach for induction machines," *Mech. Syst. Signal Process.*, vol. 107, pp. 168–182, Jul. 2018.
- [6] A. Bellini, F. Filippetti, C. Tassoni, and G.-A. Capolino, "Advances in Diagnostic Techniques for Induction Machines," *IEEE Trans. Ind. Electron.*, vol. 55, no. 12, pp. 4109–4126, Dec. 2008.
- [7] X. Dai and Z. Gao, "From Model, Signal to Knowledge: A Data-Driven Perspective of Fault Detection and Diagnosis," *IEEE Trans. Ind. Informatics*, vol. 9, no. 4, pp. 2226–2238, Nov. 2013.
- [8] D. M. J. Tax, A. Ypma, and R. P. W. Duin, "Pump Failure Detection Using Support Vector Data Descriptions BT - Advances in Intelligent Data Analysis," 1999, pp. 415–425.
- [9] Y. Shatnawi and M. Al-khassawneh, "Fault Diagnosis in Internal Combustion Engines Using Extension Neural Network," *IEEE Trans. Ind. Electron.*, vol. 61, no. 3, pp. 1434–1443, Mar. 2014.
- [10] D. Wijayasekara, O. Linda, M. Manic, and C. Rieger, "FN-DFE: Fuzzy-Neural Data Fusion Engine for Enhanced Resilient State-Awareness of Hybrid Energy Systems," *IEEE Trans. Cybern.*, vol. 44, no. 11, pp. 2065–2075, Nov. 2014.
- [11] D. Dou and S. Zhou, "Comparison of four direct classification methods for intelligent fault diagnosis of rotating machinery," *Appl. Soft Comput.*, vol. 46, pp. 459–468, Sep. 2016.
- [12] A. Soualhi, G. Clerc, and H. Razik, "Detection and Diagnosis of Faults in Induction Motor Using an Improved Artificial Ant Clustering Technique," *IEEE Trans. Ind. Electron.*, vol. 60, no. 9, pp. 4053–4062, Sep. 2013.
- [13] S. Aouabdi, M. Taibi, S. Bouras, and N. Boutasseta, "Using multi-scale entropy and principal component analysis to monitor gears degradation via the motor current signature analysis," *Mech. Syst. Signal Process.*, vol. 90, pp. 298–316, Jun. 2017.
- [14] A. Widodo and B.-S. Yang, "Support vector machine in machine condition monitoring and fault diagnosis," *Mech. Syst. Signal*

Process., vol. 21, no. 6, pp. 2560–2574, Aug. 2007.

- [15] J. Faiz and E. M. Tehrani, "Demagnetization Modeling and Fault Diagnosing Techniques in Permanent Magnet Machines under Stationary and Non-Stationary Conditions An Overview," vol. 9994, no. c, 2016.
- [16] M. Z. Ali, M. N. S. K. Shabbir, X. Liang, Y. Zhang, and T. Hu, "Machine Learning-Based Fault Diagnosis for Single- and Multi-Faults in Induction Motors Using Measured Stator Currents and Vibration Signals," *IEEE Trans. Ind. Appl.*, vol. 55, no. 3, pp. 2378–2391, May 2019.
- [17] M. Saimurugan, K. I. Ramachandran, V. Sugumaran, and N. R. Sakthivel, "Multi component fault diagnosis of rotational mechanical system based on decision tree and support vector machine," *Expert Syst. Appl.*, vol. 38, no. 4, pp. 3819–3826, 2011.
- [18] B. Asad, T. Vaimann, A. Belahcen, A. Kallaste, A. Rassõlkin, and M. N. Iqbal, "Broken rotor bar fault detection of the grid and inverter-fed induction motor by effective attenuation of the fundamental component," *IET Electr. Power Appl.*, vol. 13, no. 12, pp. 2005–2014, 2019.
- [19] C. Cortes and V. Vapnik, "Support-vector networks," *Mach. Learn.*, vol. 20, no. 3, pp. 273–297, 1995.
- [20] S. Abe, *Support vector machines for pattern classification*, vol. 2. Springer, 2005.
- [21] S. Haroun, A. N. Seghir, and S. Touati, "Multiple features extraction and selection for detection and classification of stator winding faults," *IET Electr. Power Appl.*, vol. 12, no. 3, pp. 339–346, Mar. 2018.
- [22] M. Seera, C. P. Lim, S. Nahavandi, and C. K. Loo, "Condition monitoring of induction motors: A review and an application of an ensemble of hybrid intelligent models," *Expert Syst. Appl.*, vol. 41, no. 10, pp. 4891–4903, Aug. 2014.
- [23] J. Žižka, F. Dařena, and A. Svoboda, "Random Forest," in *Text Mining with Machine Learning*, First. Boca Raton : CRC Press, 2019.: CRC Press, 2019, pp. 193–200.

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