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A Classification Approach for Induction Motor Faults Based on Empirical Mode Decomposition and Machine Learning Algorithms

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ABSTRACT

In this paper, a machine learning based approach is presented for detection and classification of faults in an induction machine. Five different classification algorithms, namely, support vector machine (SVM), decision tree, random forest, naive Bayes, and extreme gradient boosting (XGBoost), are adopted. The diagnosis of the most common types of faults such as broken bars, interturn fault and outer racing fault are considered. The current signatures under healthy and various faulty conditions are used for training and validating the models. The feature extraction step is implemented with the help of discrete wavelet transform (DWT). Following DWT, the features obtained are fed to the classification algorithms and subsequently the performance of each algorithm with respect to each fault condition is evaluated with appropriate metrics. Finally, a performance comparison is done and the most suitable classifier for reliable diagnosis of each of the fault condition is suggested.

Index Terms—Fault diagnosis, Induction machine, Fault classifier, Machine learning, Discrete Wavelet Transform

I. INTRODUCTION

Induction motors (IMs) are quite popular for their sturdiness, robustness, and low cost of maintenance. Despite being a well-matured technology, it is still prone to various kinds of faults. Many of these defects do not result in an immediate decline in system performance but, if ignored, can eventually severely damage the motor. This can lead to revenue losses for the stakeholders in terms of both replacement and unplanned downtimes. Being widely used in a variety of critical applications in various industries, it becomes necessary to have a reliable diagnosing methodology to identify and mitigate the fault at an incipient stage. The various methods of fault diagnosis in IMs include vibration analysis, motor current signature analysis, thermography, and acoustic monitoring. The vibration analysis involves the measurement of vibration signals that require additional sensors and correct positioning of sensors. The motor current signature analysis requires current signal capturing, which is also a part of monitoring of energy consumption and protecting the machine in the event of overloading. Thermography requires temperature estimation in various parts of the machine through sensors or imaging, which might add to the cost of the facility. Acoustic monitoring has the issue of filtering out the components which might not be the fault-inducing components. Hence, motor current signature analysis is one potential choice for condition monitoring of machines with a greater impact on the industrial sector as it is an inherent part of the whole system requiring only the current sensor which is part of diagnostics.

In addition, several data-driven approaches that leverage machine learning and deep neural network models for fault classification have been devised by researchers for IM fault diagnosis [1–6]. The research works presented in [7–9] propose solutions that are focused on identifying broken rotor bars in induction machines based on support vector machine (SVM) and k-nearest neighbor (k-NN) classifiers, respectively. A methodology is formulated in [6] for detecting co-occurring faults such as eccentricity faults and broken rotor bars from start-up current signal using minimum Mahalanobis distance classifier and k-NN classifier. In [10–14], a deep learning-based approach comprising convolutional filters and SVM, for fault diagnosis in IMs is explored.

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A comparison of SVM, k-NN, and multi-layer Perceptron for detecting bearing failures at different load and voltage conditions has been done in [15].

Feature extraction method is critical for model performance. Several methods based on Fourier transform [16–18], wavelet transform (WT) [19, 20], power spectral density [21] and some advanced methods based on convolutional neural networks (CNN) [22–24] have been proposed by scholars for feature extraction. Among the proposed solutions WT and Discrete WT (DWT) are the most commonly preferred [25] for IM diagnosis owing to its ease of use [26].

Researchers in [27] have applied DWT for detecting rotor bar faults in IMs. In [28, 29], wavelet packet decomposition is used for feature extraction in their neural network-based approach for fault diagnosis in IM. Wavelet packet decomposition is another common technique that provides higher frequency resolution compared to DWT at the expense of higher computational costs.

The major contribution of this work lies in presenting a DWT-based machine learning tool for IM fault classification. Multiple machine learning algorithms are trained on the features extracted using DWT. For various combinations of defects, both multiclass classification and binary classification have been investigated. The results of each algorithm's performance comparison are given.

This paper is organized as follows: In section II, the experimental setup used for fault simulation and data acquisition is explained. In section III, the proposed methodology is detailed. Section IV deals with the feature extraction using DWT. Section V gives a brief summary of five different classifiers, namely, SVM, decision tree, random forest, naive Bayes, and extreme gradient boosting (XGBoost), and section VI provides a comparison of the performance of all the classifiers using three different metrics namely accuracy, recall, and precision.

II. EXPERIMENTAL SETUP

The experimental setup shown in Fig. 1 consists of a dynamometer and two IMs—one for simulating faults and the other to use as reference. Both are 3 ϕ, 1 HP, 415 V, 50 Hz, 4 pole, and 1440 rpm machines. Dynamometer rating is 0.75 kW, 1500 rpm, 0.5 kg-m with an excitation voltage of 85 V.

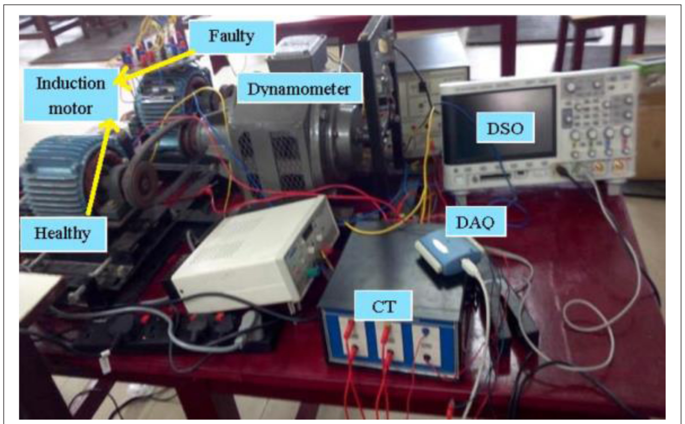

Fig. 1. (a) Experimental setup.

Stator current monitoring and storage is done using Digital Storage Oscilloscope DSO-X 3024A MY54020518 - 200 MHz, and the data is further processed using MATLAB.

III. PROPOSED METHODOLOGY

The proposed methodology has five major steps: (i) Fault simulation, (ii) Data collection, (iii) Feature extraction, (iv) Classification, and (v) Performance evaluation. Fig. 2 shows the systematic approach used in the present work.

The methodology begins with simulating the faults in an IM, which was tested and verified to be in healthy condition. Test motor is

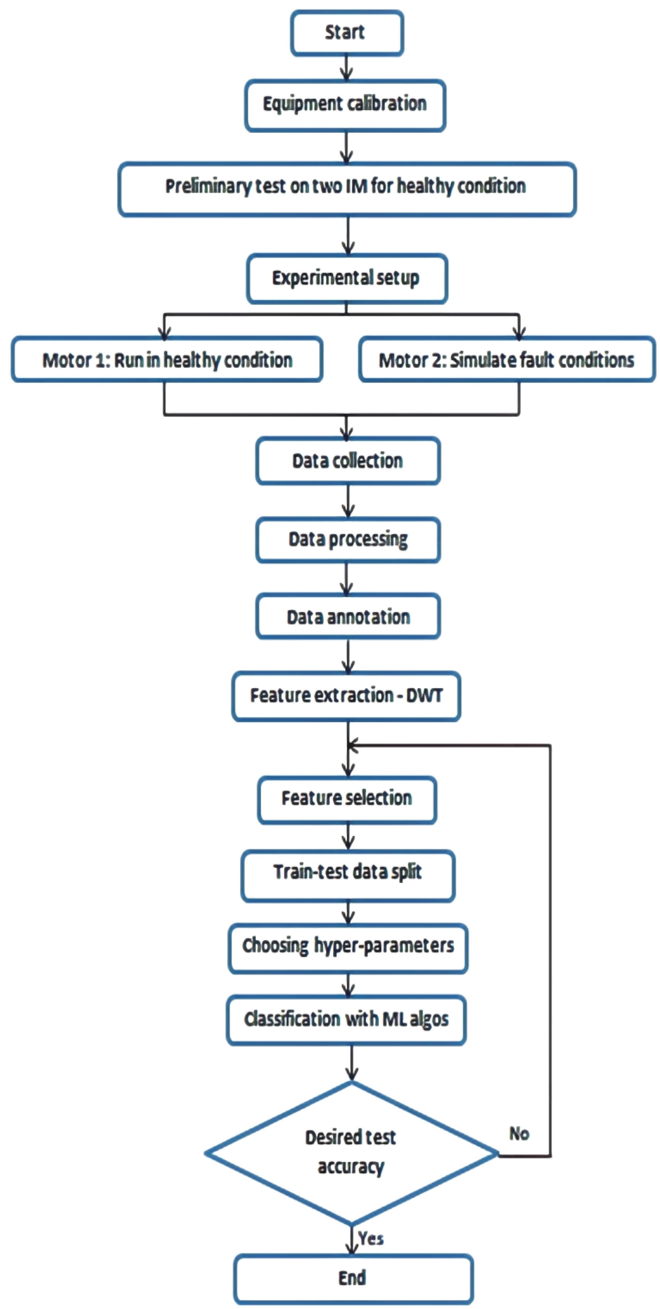

Fig. 2. Flowchart of the proposed methodology.

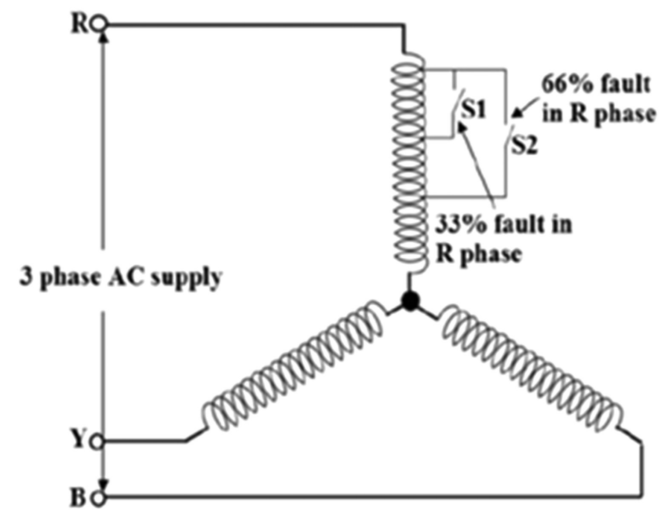

Fig. 3. Creation of inter turn short circuit fault.

provided with tapings at different turns of the stator winding. Interturn short circuit fault is generated by shorting the one-way switches that are connected between these terminals as shown in Fig. 3. The test motor has 12 turns/phase, one-third of the fault is created by shorting four turns and two-thirds of the fault is created by shorting eight turns.

Broken rotor bar fault is created by punching a hole of diameter 1.6 mm and depth 5 mm on the rotor as shown in Fig. 4. This is repeated for three rotor bars, and stator current signal is acquired under all three conditions. Outer racing fault is emulated by drilling holes in the outer race of the bearing as shown in Fig. 5. To ensure diversity, data is collected for various load and no-load conditions.

The next stage involves extracting relevant features from the signal using DWT. The detail coefficients and approximation coefficients obtained would serve as input to our subsequent classification step. Haar and Daubechies 10 were compared, and Haar has been used based on the lower number of decomposition levels.

Classification step is implemented by use of five classification algorithms, namely, 1. support vector machine, 2. naive Bayes, 3. decision tree, 4. random forest, and 5. XGBoost. The data are randomly shuffled and split into train and test data in the ratio of 3:1. Lastly, the performance of the models are evaluated on the test data using appropriate evaluation metrics and the results obtained are presented in detail in section VI.

Fig. 4. Broken bar fault in rotor.

IV. DISCRETE WAVELET TRANSFORM FOR FEATURE EXTRACTION

The stator current of this test motor is acquired under healthy and faulty condition with the sampling frequency of 20000Hz and with 2000 data samples as shown in Fig. 6a and b. The interturn fault is created externally by short circuiting the terminals of the tapings.

The current frequency (fst) appearing corresponding to the interturn short circuit faults is expressed as

fst = fs(m/p(1 − s) ± k) (1)

From figures, for the same loading condition, the difference between the healthy and faulty conditions of the IMs is shown only in amplitude. There is no other information about healthy and faulty IMs. But every change in the IM is directly reflected in the IMs stator current, and therefore it is necessary to extract the features of the signals using some signal processing techniques.

Discrete Wavelet transform is a multi-resolution analysis technique that provides a time-frequency domain representation of the signal. The original signal is decomposed into a number of detailed signals and one approximation signal by recursively passing through several levels of low pass and high pass filters derived from the mother wavelet. Discrete wavelet transform provides good time resolution and poor frequency resolution at high frequency and conversely, it provides poor time resolution and good frequency resolution at low frequencies. In each level of decomposition, the sequence is simultaneously passed through a digital low pass filter and digital high pass filter with impulse responses of *h*[*n*] and *g*[*n*], respectively.

$$y_{high}[k] = \sum_{n} x[n] \bullet g[2k - n] \quad (2)$$

$$y_{low}[k] = \sum_{n} x[n] \bullet h[2k - n] \quad (3)$$

Fig. 5. Bearing fault.

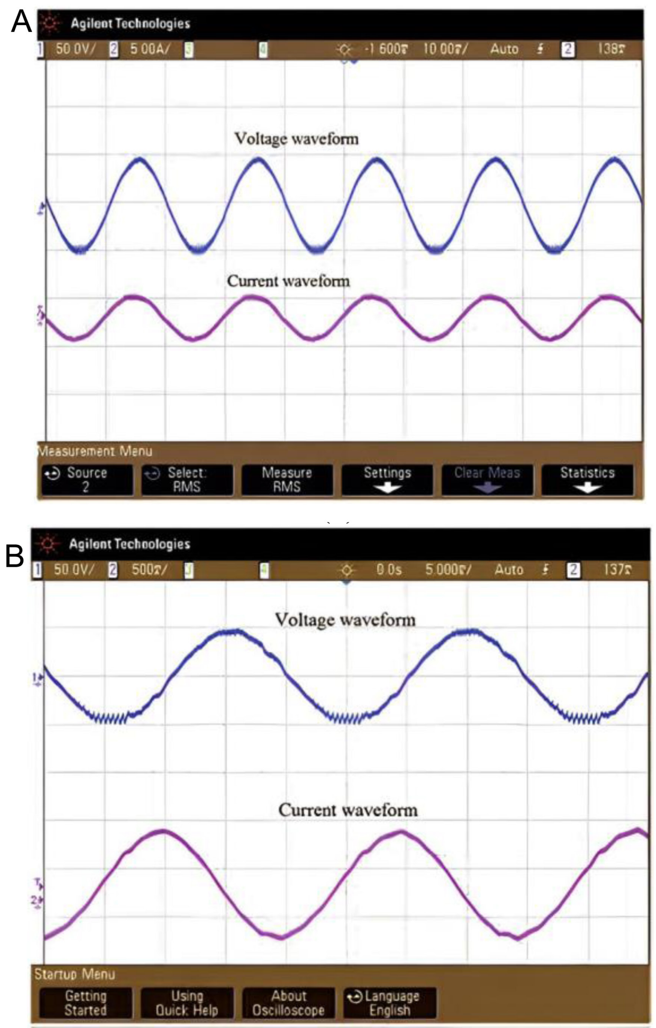

Fig. 6. (a) Measured voltage and current for healthy and (b) measured voltage and current for faulty condition.

The approximation signal can be used to isolate the faulty component after a suitable decomposition level. But with the machine learning algorithms, a single level of decomposition is sufficient to extract the features is sufficient to attain good accuracy. The overall process followed in this work is shown in Fig. 7.

Wavelet transform represents a signal with detail and approximation coefficients. These components cover the entire frequency spectrum with different band widths and whose frequency band depends on the sampling frequency (fs). The highest band covers the frequency range fs/2 to fs/4; whereas the lowest band depends upon the decomposition levels. For next decomposition levels, the center frequency and band width will be halved.

The sampling frequency of the data samples decides the frequency band of the wavelet coefficients. The Multi-Resolution Analysis decomposition levels and corresponding frequency ranges are given in Table I.

Using equation (1), the fault harmonic frequencies corresponding to the interturn fault created are frequencies 75, 100, 125, 150, 175, 200, 225Hz, etc. They are covered in the frequency ranges with

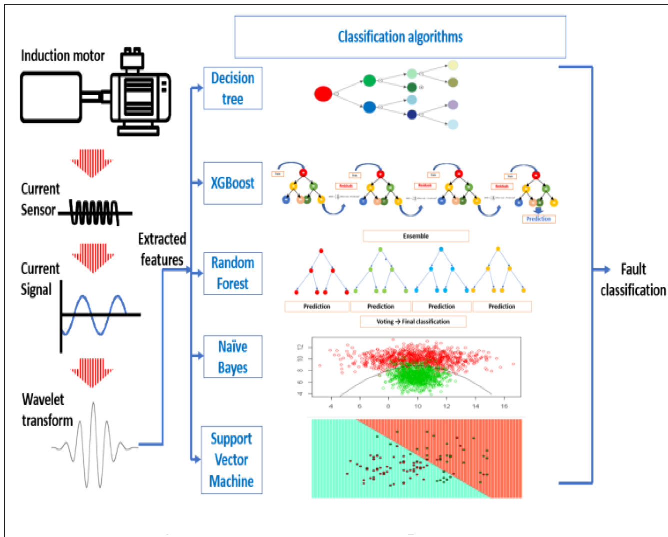

Fig. 7. The classification process.

decomposition levels 6, 7, and 8. Usually, the fault identification can be done from the wavelet coefficients of the higher decomposition levels.

The wavelet coefficients of different decomposition levels for faulty and healthy current shown in Fig. 6a and b are shown in Fig. 8.

V. CLASSIFICATION ALGORITHMS

The classification algorithms chosen for this work are detailed as follows.

A. Decision Tree

Decision tree is a non-parametric supervised learning model where a tree-like structure mimics the human decision-making thought process. Starting from the root node, each branch represents a decision made and the internal nodes represent the attributes. The leaf node represents the outcome of the model. The model is easy to interpret, making it quite advantageous.

In this work, the information gain and entropy are utilized as the criterion for accessing the impurity of a node in the tree. Entropy can be explained as a measure of randomness. The expression for entropy is given as follows

TABLE I. PERFORMANCE OF MODELS WITH RESPECT TO VARIOUS FAULTS

Decomposition Levels	Frequency Range (Hz)
1	10k–5k
2	5k–2.5k
3	2.5k–1.25k
4	1.25k–0.625k
5	625–312.5
6	312.5–156.25
7	156.25–78.125
8	78.125–39.0625

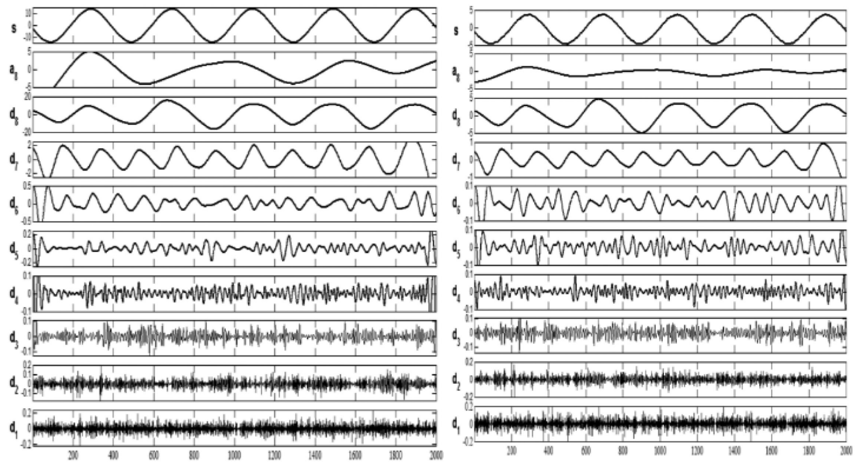

Fig. 8. Decomposition levels of faulty and healthy motor.

$$E(S)=\sum_{i=1}^{c}-p_i\log_2 p_i \tag{4}$$

where S is the current node state, p_i is the probability of event i in the node of state S. It can be noted from Fig. 9 that entropy is lower in nodes which are more homogeneous. The information gain and entropy are related as follows:

$$IG(Y,X)=E(Y)-E(Y\,|\,X) \tag{5}$$

where IG is the information gain and E is the entropy. $E(Y)$ refers to the case where there is no impurity and $E(Y|X)$ is the entropy of the node under consideration. The tree continues to branch out until IG cannot be increased any further.

B. Random Forest Classifier

Random forest as shown in Fig. 10 is an ensemble technique that employs multiple decision tree classifiers. These classifiers will put forth their predictions and the class with the most votes is considered as the final prediction. The precision of the overall model increases with the number of individual models.

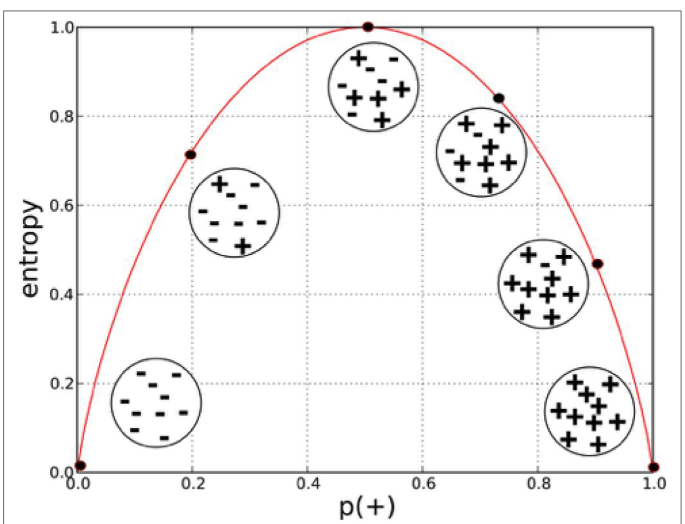

Fig. 9. Entropy for decision tree.

Diversity between individual models is ensured by using a technique called bagging where each model is trained with a subset of the original dataset. Further, each model is trained on only a subset of the features to induce diversity between the models. Random forest classifiers are thus immune to overfitting and quite reliable.

C. Extreme Gradient Boosting

The term "boosting" refers to a class of algorithms which builds a strong learner from a bunch of weak learners. Extreme Gradient Boosting is a parallelized optimized implementation of Gradient Boosting (GB) Algorithm. In GB, learners are added incrementally to the classifier in order to reduce the error produced by its predecessor.

Assuming a weak learner model $F_m(x)$, let " $\check{y}_m$ " be the prediction made.

$$\check{y}_m=F_m(x) \tag{6}$$

Subsequently estimators $h_m(x)$ are added to the base model $F_m(x)$.

$$F_{m+1}(x)=F_m(x)+h_m(x) \tag{7}$$

If $L(y_m,\check{y}_m)$ is the loss function, then the estimator is given as negative gradient of $L(y_m,\check{y}_m)$ with respect to function F(x),

$$h_m(x)=-\frac{\partial L(y,\check{y})}{\partial F} \tag{8}$$

which makes the next model as

$$F_{m+1}(x)=F_m(x)-\frac{\partial L(y,\check{y})}{\partial F} \tag{9}$$

After many stages, the model accuracy gradually increases, generating a robust model.

D. Support Vector Machine

Support vector machine is a popular machine learning model used for classification as well as regression tasks. Support vector machine creates a hyperplane in the input space which functions as a separator between the data points corresponding to different classes. The multiclass SVM models are generally implemented by two methods: one-versus-all method and one-versus-one (OVO) method. In

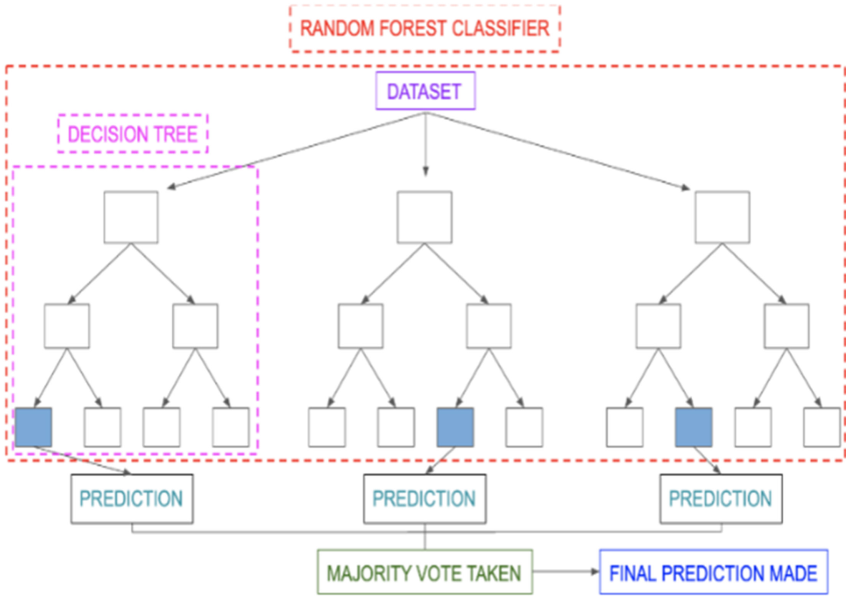

Fig. 10. Random forest classifier.

this work, OVO approach has been used, where N(N + 1)/2 models are created if there are N classes to be classified. To account for non-linearity in the data points, Gaussian RBF has been has been chosen as the kernel for the SVM model. Various values of hyperparameters viz. kernel coefficient gamma and regularization factor C were analyzed and the optimal results obtained were found with gamma as 1/(input_features_count × input_feature_variance) and regularization factor C as 1.0.

E. Naive Bayes Classifiers

Naive Bayes classifiers are a class of algorithms that are based on the Bayes theorem. Bayes theorem provides a way for calculating the posterior probability of a class ($P(y|x)$) given the predictor (input features) if the prior probability of the class ($P(x)$), prior probability of predictor ($P(y)$), and posterior probability of a predictor given the class ($P(x|y)$) are known.

$$P(y\,|\,x) = \frac{P(x\,|\,y) \times P(y)}{P(x)} \tag{10}$$

Naive Bayes assumes the features are non-correlated, and their contributions to the outcome are equal. Gaussian naive Bayes classifier which assumes that the input features conform to a Gaussian distribution was used. Here the probability of a predictor given the class take the below form,

$$P(x\,|\,y) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}(\frac{x-\mu}{\sigma})^2} \tag{11}$$

where μ and σ are mean and standard deviation, respectively, for each feature.

VI. RESULTS AND DISCUSSION

Accuracy, precision, and recall are used as the performance metrics for evaluation. Precision gives a measure of the confidence of the model when a fault is detected. High precision means lesser chance of false alarms. On the other hand, with high recall less faults go unnoticed, but not all the fault detections may necessarily be a case of true positive. The results of classification are given in Table II.

Precision = True positives/(True positives + False positives)

Recall = True positives/(True positives + False negatives).

A. Broken Rotor Bar

The data distribution for broken rotor bars is indicated in Table III. As it can be observed from Table I, decision tree and random forest classifiers provide better accuracy in detecting broken bar faults compared to other models. Although random forest has marginally better accuracy, decision tree is able to provide significantly higher precision. This means with decision tree the chances of getting false alarms are considerably lesser. Furthermore, decision tree is far less computationally expensive compared to random forest. Therefore, decision tree is the ideal choice for cases with computational resource constraints. In the absence of such constraints, random forest can be a better choice for detecting single, double, and triple broken rotor bars.

B. Interturn Fault

The data distribution for interturn fault is indicated in Table IV. In case of interturn fault, random forest algorithm is outperforming every other algorithm under consideration in terms of accuracy, precision, as well as recall, making it the clear choice.

C. Bearing Fault

The data distribution for bearing fault is indicated in Table V. As for detecting bearing fault, decision tree, XGBoost, and random forest—all three are able to provide 100% accuracy, precision, and recall for classifying bearing fault. Nevertheless, when considering the computational resources involved, decision tree is more suitable for the application.

D. Multi-fault Detection: Broken Bar, Interturn Fault, and Bearing Fault

The data distribution for all the faults considered is indicated in Table VI. For multiclass classification with three cases of broken bar

TABLE II. PERFORMANCE OF MODELS WITH RESPECT TO VARIOUS FAULTS

Motor Faults	Algorithm	Accuracy (%)	Precision (%)	Recall (%)
1 broken bar	SVM	52.04	55	34
	Naive Bayes	58.77	67	38
	Decision trees	90.52	91	90
	XGBoost	88.53	85	88
	Random forest	92.12	85	88
1 and 2 broken bar	SVM	36.65	37	32
	Naive Bayes	40.84	41	40
	Decision trees	87.57	88	88
	XGBoost	75.54	76	75
	Random forest	88	87	88
1, 2, and 3 broken bar	SVM	28.04	28	19
	Naive Bayes	31.25	32	28
	Decision trees	84.99	87	86
	XGBoost	75	82	69
	Random forest	85.24	84	85
Interturn fault	SVM	84.2	84	82
	Naive Bayes	91.91	90	92
	Decision trees	94.22	95	94
	XGBoost	94.97	94	95
	Random forest	99.3	99	97
Bearing fault	SVM	87.96	83	90
	Naive Bayes	97.11	99	96
	Decision trees	100	100	100
	XGBoost	100	100	100
	Random forest	100	100	100
Multi-fault:1, 2, 3 broken bar and Interturn and Bearing fault	SVM	23.18	23	19
	Naive Bayes	26.27	29	30
	Decision trees	62.76	63	63
	XGBoost	87.86	88	89
	Random forest	88.1	89	88

TABLE III. DATA DISTRIBUTION—SINGLE, DOUBLE, AND TRIPLE BROKEN BAR FAULT DETECTION

Test Dataset Distribution			
1 Broken Bar Fault	2 Broken Bar Fault	3 Broken Bar Fault	Healthy
1013	1032	1016	951

TABLE IV. DATA DISTRIBUTION—INTERTURN FAULT DETECTION

Test Dataset Distribution	
Interturn Fault	Healthy
2132	1888

TABLE V. DATA DISTRIBUTION—BEARING FAULT DETECTION

Test Dataset Distribution	
Bearing fault	Healthy
1018	1999

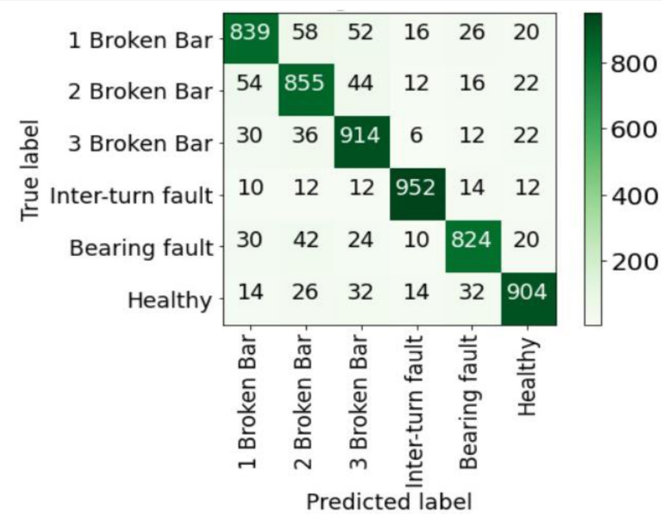

Fig. 11. Confusion matrix—XGBoost—single, double, triple broken bar fault, interturn fault, and bearing fault.

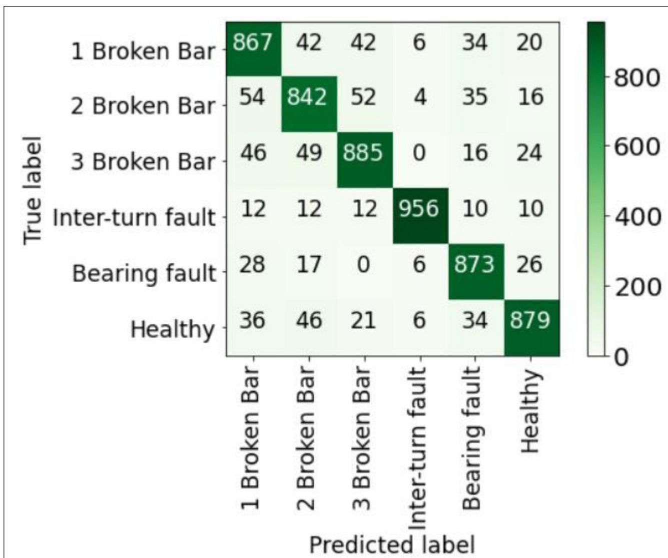

Fig. 12. Confusion matrix—random forest—single, double, triple broken bar fault, interturn fault, and bearing fault.

TABLE VI. DATA DISTRIBUTION—SINGLE, DOUBLE, TRIPLE BROKEN BAR, INTERTURN, BEARING FAULT DETECTION

Test Dataset Distribution					
1 Broken Bar Fault	2 Broken Bar Fault	3 Broken Bar Fault	Interturn Fault	Bearing Fault	Healthy
1011	1003	1020	1012	950	1022

(1, 2, and 3), interturn fault [30], and bearing fault, both XGBoost and random forest provide close results. Fig. 11 and 12 provide the results, respectively. Since computational complexity is comparable, either of the models can be used for this scenario.

VII. CONCLUSION

In this paper, machine learning techniques are explored for classification of some of the commonly occurring faults in IMs. The main contribution of this paper is fault-related feature extraction from the current signal using DWT and the use of five classifier algorithms for IM fault classification. The methodology is validated with various faults like one broken bar fault, two broken bar fault, three broken bar fault, stator fault, bearing fault, and even with multi-faults.

The following conclusions are drawn from the results obtained.

- Even with a single level of decomposition in DWT, machine learning algorithms can detect the presence of faults effectively, thereby saving computational costs.
- The choice of model should be made considering the type of fault to be detected. The performance of models varies considerably between different fault conditions and therefore choosing the right model is critical.
- For detection of single and multiple broken rotor bar faults, a less computationally intensive algorithm such as decision tree can be chosen over ensemble methods with very minimal sacrifice in accuracy.
- For detection of co-occurring multiple faults, ensemble methods like random forest and XGBoost provide better overall performance.

Though the offline results of the proposed method are only presented in this paper, it is well suited for online implementation as well. To automate the process of condition monitoring of motors, data preprocessing is required and in this paper, level 1 decomposition with DWT is used. The algorithmic effort for DWT would offset the precision of the fault classification.

Further, the work could be extended by applying deep learning techniques such as CNNs with increased data collection suited for critical industrial applications employing IMs.

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REFERENCES

1. J. Xie, Z. Li, Z. Zhou, and S. Liu, "A novel bearing fault classification method based on XGBoost: The Fusion of deep learning-based features and empirical features," *IEEE Trans. Instrum. Meas.*, vol. 70, pp. 1–9, 2021. [CrossRef]
2. K. Laadjal, H. R. P. Antunes, M. Sahraoui, F. Bento, and A. J. M. Cardoso, "Online diagnosis and discrimination of stator faults in six-phase induction motors based on voltage symmetrical components," *IEEE Trans. Transp. Electrif.*, vol. 9, no. 2, pp. 3115–3126, 2023. [CrossRef]
3. A. L. Dias, A. C. Turcato, G. S. Sestito, D. Brandao, and R. Nicoletti, "A cloud-based condition monitoring system for fault detection in rotating machines using PROFINET process data,", *Computers in Industry*, vol. 126, p. 103394, 2021. [CrossRef]
4. X. Chen, and Z. Feng, "Tacholess speed estimation for rotating machinery fault diagnosis of induction motor drivetrain," *IEEE Trans. Power Electron.*, vol. 39, no. 4, pp. 4704–4713, 2024. [CrossRef]
5. A. K. Das, S. Das, A. K. Pradhan, B. Chatterjee, and S. Dalai, "RPCNNet: A deep learning approach to sense Minor stator winding Interturn Fault severity in induction motor under variable load condition," *IEEE Sens. J.*, vol. 23, no. 4, pp. 3965–3972, 2023. [CrossRef]
6. G. H. Bazan, P. R. Scalassara, W. Endo, A. Goedtel, W. F. Godoy, and R. H. C. Palácios, "Stator fault analysis of three-phase induction motors using information measures and artificial neural networks," *Electr. Power Syst. Res.*, vol. 143, pp. 347–356, 2017. [CrossRef]
7. H. Keskes, and A. Braham, "Recursive undecimated wavelet packet transform and DAG SVM for induction motor diagnosis," *IEEE Trans. Ind. Inform.*, vol. 11, no. 5, pp. 1059–1066, 2015. [CrossRef]
8. M. Singh, and A. G. Shaik, "Incipient fault detection in stator windings of an induction motor using Stockwell transform and SVM," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 12, pp. 9496–9504, 2020. [CrossRef]
9. W. Chen, J. Li, Q. Wang, and K. Han, "Fault feature extraction and diagnosis of rolling bearings based on wavelet thresholding denoising with CEEMDAN energy entropy and PSO-LSSVM," *Measurement*, vol. 172, p. 108901, 2021. [CrossRef]
10. M. Abdelmaksoud, M. Torki, M. El-Habrouk, and M. Elgeneidy, "Convo lutional-neural-network-based multi-signals fault diagnosis of induction motor using single and multi-channels datasets," *Alex. Eng. J.*, vol. 73, pp. 231–248, 2023. [CrossRef]
11. T. T. Vo, M. K. Liu, and M. Q. Tran, "Harnessing attention mechanisms in a comprehensive deep learning approach for induction motor fault diagnosis using raw electrical signals," *Eng. Appl. Artif. Intell.*, vol. 129, p. 107643, 2024. [CrossRef]
12. H. Fan, Z. Ren, X. Cao, X. Zhang, and J. Huang, "A GTI&Ada-Act LMCNN method for intelligent fault diagnosis of motor rotor-bearing unit under variable conditions," *IEEE Trans. Instrum. Meas.*, vol. 73, pp. 1–14, 2024. [CrossRef]
13. H. Pu, S. Teng, D. Xiao, L. Xu, Y. Qin, and J. Luo, "Compound fault diagnosis of rotating machine through label correlation modeling via graph convolutional neural network," *IEEE Trans. Instrum. Meas.*, vol. 73, pp. 1–10, 2024. [CrossRef]
14. R. Rajabioun, M. Afshar, M. Mete, Ö. Atan, and B. Akin, "Distributed bearing fault classification of induction motors using 2-D deep learning model," *IEEE J. Emerg. Sel. Top. Ind. Electron.*, vol. 5, no. 1, pp. 115–125, 2024. [CrossRef]
15. W. Sun, R. Zhao, R. Yan, S. Shao, and X. Chen, "Convolutional discriminative feature learning for induction motor fault diagnosis," in *IEEE Trans. Ind. Inform.*, vol. 13, no. 3, pp. 1350–1359, 2017. [CrossRef]
16. G. H. Bazan, P. R. Scalassara, W. Endo, and A. Goedtel, "Information theoretical measurements from induction motors under several load and voltage conditions for bearing faults classification," *IEEE Trans. Ind. Inform.*, vol. 16, no. 6, pp. 3640–3650, 2020. [CrossRef]
17. J. Fu, and G. Che, "Fusion fault diagnosis model for six-rotor UAVs based on conformal Fourier transform and improved self-organizing feature map," *IEEE Access*, vol. 9, pp. 14422–14436, 2021. [CrossRef]
18. C. G. Dias and L. C. d. Silva, "Induction motor speed estimation based on Airgap flux measurement using Hilbert transform and fast Fourier transform," *IEEE Sensors Journal*, vol. 22, no. 13, pp. 12690-12699, 1 July 1, 2022. [CrossRef]
19. A. Almounajjed, A. K. Sahoo, and M. K. Kumar, "Diagnosis of stator fault severity in induction motor based on discrete wavelet analysis,", *Measurement*, vol. 182, p. 109780, 2021. [CrossRef]
20. M. -Q. Tran, M. -K. Liu, Q. -V. Tran, and T. -K. Nguyen, "Effective fault diagnosis based on wavelet and convolutional attention neural network for

induction motors," *IEEE Trans. Instrum. Meas.*, vol. 71, pp. 1–13, 2022. [CrossRef]

21. A. Polat, A. Yılmaz, and L. T. Ergene, "Investigation of the effects of eccentricity on induction motor via multi-resolution wavelet analysis," *Electrica*, vol. 18, no. 2, pp. 187–197, 2018. [CrossRef]
22. M. Akar, and İ. Çankaya, "Diagnosis of static eccentricity fault in permanent magnet synchronous motor by on-line monitoring of motor current and voltage," *Electrica*, vol. 9, pp. 951–958, 2009.
23. D. T. Hoang, and H. J. Kang, "A motor current signal-based bearing fault diagnosis using deep learning and information Fusion," *IEEE Trans. Instrum. Meas.*, vol. 69, no. 6, pp. 3325–3333, 2020. [CrossRef]
24. J. Feng, Y. Yao, S. Lu, and Y. Liu, "Domain knowledge-based deep-broad learning framework for fault diagnosis," *IEEE Trans. Ind. Electron.*, vol. 68, no. 4, pp. 3454–3464, 2021. [CrossRef]
25. X. Zhao, M. Jia, P. Ding, C. Yang, D. She, and Z. Liu, "Intelligent fault diagnosis of multichannel motor–rotor system based on multimanifold deep extreme learning machine," in *IEEE ASME Trans. Mechatron.*, vol. 25, no. 5, pp. 2177–2187, 2020. [CrossRef]
26. R. Yan, R. X. Gao, and X. Chen, "Wavelets for fault diagnosis of rotary machines: A review with applications,", *Signal Processing*, vol. 96, No. A, pp. 1–15, 2014. [CrossRef]
27. Polikar, "The Wavelet tutorial." Available: http://users.rowan.edu/~polikar/WTtutorial.html. [Accessed: September 19, 2019].
28. H. Talhaoui, T. Ameid, O. Aissa, and A. Kessal, "Wavelet packet and fuzzy logic theory for automatic fault detection in induction motor," *Soft Comput.*, vol. 26, no. 21, pp. 11935–11949, 2022. [CrossRef]
29. R. D. Pawan, and R. Dhiman, "Motor imagery signal classification using Wavelet packet decomposition and modified binary grey wolf optimization,", *Measurement: Sensors*, vol. 24, p. 100553, 2022. [CrossRef]
30. W. Abitha Memala, and V. Rajini, "Parametric method based inter-turn incipient short circuit stator fault detection of induction motor," *Indian J. Sci. Technol.*, vol.: 9, No.: 43, pp. 1–6, 2016. [CrossRef]

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