An Improved Stator Winding Short-circuit Fault Diagnosis using AdaBoost Algorithm

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Abstract—**Brushless DC (BLDC) motors, bearing the characteristics of permanent magnet synchronous machines, have gained immense popularity in industrial applications due to its excellent efficiency and ease in control over conventional DC motors. Stator related faults are the most common types of faults in BLDC motors while operating under a higher loading and complex condition. Conventional machine learning (ML) classifiers such as- Support Vector Machines (SVM), k-nearest neighbors (KNN), Naïve Bayes (NB) classifiers fail to obtain optimum accuracy when there are abrupt changes in health states of the BLDC motor. Especially the classification of weak health features ends up with an erroneous result. Boosting techniques allow adding weights to weak features and a better result in classification. This study presents an improved stator related fault classification of BLDC Motor using AdaBoost technique. Several parameters of AdaBoost algorithm are optimized and implemented along with Random Forest (RF) classifier in order to determine a developed algorithm for fault classification.**

Keywords—**AdaBoost, BLDC motor, CBM, Classification**

I. INTRODUCTION

An equipment failure in industrial applications not only hampers the productivity but also causes an increase in the exhaustive cost of a system. Despite having a good product design and assembling, due to certain load, stress or operating time, equipment wears out over time and exhibit aberrant response compared to what is expected to be normal. If not monitored properly, even a small equipment failure can lead to a catastrophic breakdown of a system. This emphasizes the necessity of a proper maintenance scheme to assure a satisfactory level of system reliability, lower environmental risk and maximize availability. Several maintenance strategies have been adopted by engineers over a long period of time starting from corrective maintenance (CM) to today's preventive maintenance (PM). PM involves the condition-based maintenance (CBM) of a system that where a system's state of health (SOH) is continuously monitored by analyzing different sensor data [1]. Based on the type of system, the sensor data can be of various types such as- vibration, temperature, current, voltage, etc. After sensing data, signals are processed using different techniques, features are extracted, and dominant features are selected for diagnostics and future prognostics. Diagnostics is the key aspect of CBM as it deals with fault identification, fault isolation and fault classification. Therefore, in order to plan a proper CBM scheme, sensor data and selected features should be handled properly [2].

BLDC motor is a special type of DC motor that does not have a brush for commutation. Due to this lack of a mechanical part, commutator, it lasts long as well as shows higher efficiency, better torque-current ratio and an overall precise control scheme. Also, due to the confinement of internal components, electromagnetic interference and noise are also at a marginal level in BLDC motors. These features of BLDC motor have made this equipment to be broadly used in many modern engineering fields such as robotics, automation, transportation etc. Since both the electrical and mechanical characteristics are present in this motor, it shows several faults such as- stator winding short-circuits, broken rotor bar, eccentricity, bent shaft etc. These faults can be diagnosed by monitoring currents, temperatures, vibrations, noises etc. [3]. Many studies have shown detection and isolation of rotary machinery faults through different signal processing techniques. However, classifying the faults and finding robust decision regions for those faults cannot be predetermined. This is because of the differences in unique operating condition environments as well as many other internal and external factors affecting the operation of equipment. Due to the complex operating conditions of different systems, not all rotary machines give an identical vibration response, even though, they are of similarly rated parameters. Hence, the extracted features from the sensor data also vary from one equipment to another. It is a necessity, to evaluate one equipment's vibration response in order to assess the SOH of the system [4,5].

In this study, an internal permanent magnet (IPM) type motor is used where the rotor is the permanent magnet and the stator is the conductor coil working as electromagnets. Based on the rotor position, the stator is excited using a three-phase pulse-width modulation (PWM) type signals. In worse cases, when the motor is operating under a higher load or there is an overflow of current, the stator windings are prone to breakdown and causing some short-circuits in the windings, known as inter-turn short circuit fault. Inter-turn short-circuit causes several effects in the motor parameters including an increase in line currents, an increase in temperature, abrupt changes in vibration etc. [5,6].

Boosting has been quite popular lately for the improvement of many machine learning algorithms and acquire a better fault classification of machinery. X. Zheng et. al. reported AdaBoost-SVM for the fault diagnosis of Wind Power Converters [7]. Patil et. al. used Decision Tree and AdaBoost for the fault diagnosis of bearings [8]. Liu et. al. proposed a wireless network diagnosis model using SVM with radial basis function kernel and AdaBoost [9]. Ignacio et. al. used several classifiers i.e. NB, DT etc. with AdaBoost to classify imbalanced small data of induction motors [10]. However, no complete study has been reported till date for a proper fault classification of IMP-BLDC motors.

In this investigation, three states of motor health are assessed: (a) Healthy state, (b) Incipient failure state, and (c) Severe failure state. A healthy state is considered when the motor operates in a normal operating condition with recommended parameters from the manufacturer. Incipient failure state is the first stage when the motor starts to deviate

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from the normal operating condition, it can also be called as fault building stage. And, severe failure state is the near-breakdown state of the motor. Vibration samples from each operating condition are collected and several features are extracted that indicate SOH of the motor. Often these features are referred to as condition indicators (CI). Extracted CIs from different health states are classified using random forest (RF) classifier due to its ease in implementation as well as the capability of handling higher dimensions. Later, a boosting technique, AdaBoost is implemented with RF classifier to improve the accuracy of boosted classifier. Finally, the boosted classifier is compared to other classifying algorithms such as SVM, KNN, Naïve Bayes etc. There are several parameters that affect the accuracy of boosting technique. In this study, an optimum parameter selection method for AdaBoost has been described and presented in order to achieve higher accuracy with an acceptable computational cost.

II. Overview of Classifiers & AdaBoost

A. Support Vector Machine (SVM)

SVM is a discriminative classifier popularly used in fault detection and diagnostics (FDD) based on some labelled (supervised) data. In case of linearly separable patterns, SVM finds data points that are closest in distance and classifies them using a hyperplane. Otherwise, it uses kernel function to distribute data in a new space and find the support vectors. Hyperplane is defined by $\boldsymbol{w}^T x + b = 0$; a training set, $X = \{(x_i, y_i)\}, i = 1,2,3 \dots\dots n$. Here, $\boldsymbol{w}$ is the normal vector of hyper-pane and b is added bias. When the hyperplane separates the data satisfying maximum margin between the nearest data points, x_i, then it is called the optimum satisfying hyperplane [11]. In case of linear hyperplane, the maximum separable hyperplane can be calculated by minimizing $\boldsymbol{w}^T\boldsymbol{w}/2$ given the condition $y_i(\boldsymbol{w}^T x_i + b) \geq 1$. Some of the common kernel functions are listed in TABLE I:

TABLE I. Kernels for SVMs

Kernel Functions	Mathematical Expressions
Linear	$K(x_i, x_j) = x_i^T x_j$
Polynomial	$K(x_i, x_j) = (x_i^T x_j + l)^d$
Radial Basis Function	$K(x_i, x_j) = e^{(-\lvert x_i - x_j\rvert^2/2\sigma^2)}$
Sigmoid	$K(x_i, x_j) = \tanh(\beta x_i^T x_j + b)$

B. K Nearest Neighbours (KNN)

It is one of the most fundamental and simplest classification methods. The easiest way to define KNN is the assumption that “similar things exist in close proximity”. In this classification technique, similar data points are classified into a single group based on the distances among them. Initially, number of neighbors, K is determined and distances to other points are measured in an ordered collection [12]. Several distance metrics are used in KNN, some of them are listed in TABLE II. Although these distance metrics are described in literature, mostly used distance metrics is Euclidean metric. Li-Yu, et al. demonstrated a further review on distance metrics [12]. After finding the nearest neighbors through distance calculation, they are labelled as initially selected data point’s class. In particular, KNN requires only a positive integer value for k and a distance metric to do the classification making the algorithm straightforward to implement.

TABLE II. Distance Metrics for KNN

Distance Metric	Mathematical Expressions
Euclidean	$d(x,y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$
Manhattan	$d(x,y) = \sum_{i=1}^{n-1}\lvert(x[i] - y[i])\rvert$
Minkowski	$d(x,y) = \left(\sum_{i=1}^{n-1}(\lvert(x[i] - y[i])\rvert)^q\right)^{1/q}$
Mahalanobis	$d(x,y) = \sqrt{\left(\frac{x_1 - y_1}{\sigma_1}\right)^2 + \left(\frac{x_2 - y_2}{\sigma_2}\right)^2}$

C. Gaussian Naïve Bayes (NB)

The Naïve Bayes classifier is a heuristic supervised classification method used for the data arrangement of labelled dataset. This algorithm is based on the Bayes theorem shown in (1). The fundamental concept of this classifier is the naivety, that is, all the elements in the dataset are mutually independent, or in other words, each attribute’s probability is independent of others.

$$P(A|B) = \frac{P(B|A) \times P(A)}{P(B)} \tag{1}$$

$$P(C = C_i | A_1 = a_1 \dots\dots A_k = a_k) = \frac{P(A_1 = a_1 \dots\dots A_k = a_k \mid C = C_i)\, P(C = C_i)}{P(A_1 = a_1 \dots\dots A_k = a_k)} \tag{2}$$

$$c = P(C = C_i)\sum_{i=1}^{k} P(A_i = a_i | C = C_i) \tag{3}$$

In (1), A is called the proposition and B is called the evidence. P(A) is called the prior probability of proposition and P(A|B) is the posterior probability of proposition. The significance of (1) is to improve P(A|B) based on the evidence, B.

(2) is a modification of (1) for NB classifier that explains the process of determining probability based on Bayes theorem, where, k is the number of features or classes the dataset has. For any given instance, the probability c is computed by using (3). C is used to label the features that are to be classified as prior probability [13].

D. Random Forest (RF)

In the technical fields such as statistical classification and regression, a significant task is to predict the categorical response of the variable based on a large number of predictors. Hence, the random forest is swift and easy to implement, which produces highly accurate predictions and can handle a very large number of input variables without overfitting. In fact, it is deliberated as one of the most accurate prediction. Even if there have a complex high-order interaction effect, random forests can produce variables for each predictor variable. Therefore, within a very short time, random forest become a major data analysis tool that develops as serious competitors to state-of-the-art methods such as boosting and support vector machines [14]. Formally, a general random forest model is shown in (4).

$$\bar{r}_n(X) = \mathbb{E}_\Theta[r_n(X,\Theta)] = \mathbb{E}_\Theta\left[\frac{\sum_{i=1}^{n} Y_i 1_{[X_i \in A_n(X,\Theta)]}}{\sum_{i=1}^{n} 1_{[X_i \in A_n(X,\Theta)]}} 1_{E_n(X,\Theta)}\right] \quad (4)$$

Here:

$\bar{r}_n = Random\ forest\ regrassion$
$X = Each\ data\ sample$
$\mathbb{E}_\Theta = Expectation\ with\ respect\ to\ the\ random\ parameter$
$\Theta =$ Total output of a randomize variable

$A_n(X,\Theta) = Cell\ of\ the\ random\ partition\ containing\ X$
$E_n(X,\Theta) = The\ event$

Next, during the construction of the tree, at each node, each candidate coordinate X (j) may be chosen with probability $P_{nj} \in (0,1)$ which implies in particular $\sum_{j=1}^{d} P_{nj} = 1$.

E. AdaBoost

In machine learning domain, boosting is a significant approach to create an accurate prediction by combining many relatively weak and inaccurate features. The AdaBoost was the first boosting algorithm which used most widely in machine learning fields. AdaBboost states a method of training with a booster classifier. The boosting is a family of algorithms which formulate weak learners to be a strong learner. A boost classier form is shown in (5):

$$F_T(x) = \sum_{t=1}^{T} \alpha_t h_t(x) \quad (5)$$

Here,

$F_T = Weak\ learner$
$x = Input\ and\ returns\ a\ value\ indicating\ the\ class\ of\ object$
$T = Classier\ is\ possitive\ if\ the\ smaple\ is\ in\ positive\ class;\ otherwise\ negetavie$
$\alpha_t = Weight$
$h_t = Weak\ hypothesis$

B. Schölkopf et al. described AdaBoost algorithm as illustrated in Fig. 1 [15].

The final or combined hypothesis H computes the sign of a weighted combination of weak hypotheses and this corresponding as a weighted majority vote of the weak hypotheses h_t where each hypothesis is assigned weight α_t [15, 16].

Input: Data Set D={$(x_1, y_1), (x_2, x_2), \dots\dots\dots (x_m, y_m)$}
Process:

1. $D_1(x) = {}^1/_m$. %Initial weight distribution.
2. $for\ t = 1, \dots\dots$T:
3. Train weak learner using distribution D_t.
4. Get weak hypothesis $h_t: \mathcal{X} \longrightarrow \{-1, +1\}$
5. Aim: Select h_t with low weighted error: $\varepsilon_t = Pr_i \sim$ Dt$[h_t(x_i) \neq y_i]$.
6. Choose $\alpha_t = \frac{1}{2}\ln(\frac{1-\varepsilon_t}{\varepsilon_t})$
7. Update, for i=1…., m:

$$D_{t+1}(i) = \frac{D_t(i)\exp(-\alpha_t y_i(x_i))}{Z_t}$$

Where Z_t is a normalization factor chosen so that D_{t+1} will be a distribution.

8. **Final Output:**

$$H(x) = sign\left(\sum_{t=1}^{T} \alpha_t h_t(x)\right)$$

Fig. 1: The boosting algorithm of AdaBoost

III. Data Description and Feature Extraction

To perform life-test of BLDC motor, a conventional generator-motor setup is chosen where the motor is coupled with a generator and some variable loadings are connected with the generator. To acquire vibration data, a piezoelectric accelerometer is mounted on top of the motor and data were continuously acquired using NI cDAQ-9178 module. Fig. 2 shows the test rig setup for BLDC motor test. TABLE III describes the BLDC motor parameters.

TABLE III. BLDC Motor Parameters

Parameter	Values
Model	BLS-24026N
Rated voltage	DC 24V
Rated torque	0.096 N.m
Rated speed	4,000 RPM±10%
Rated current	<2.5A
Rated output	40W
No load speed	5,000 RPM±10%
No load current	<0.6A

As mentioned earlier, three health states of motor are considered for this study. Fig. 3 shows the vibration samples in different states and their corresponding frequency domain representations. From the frequency domain representation,

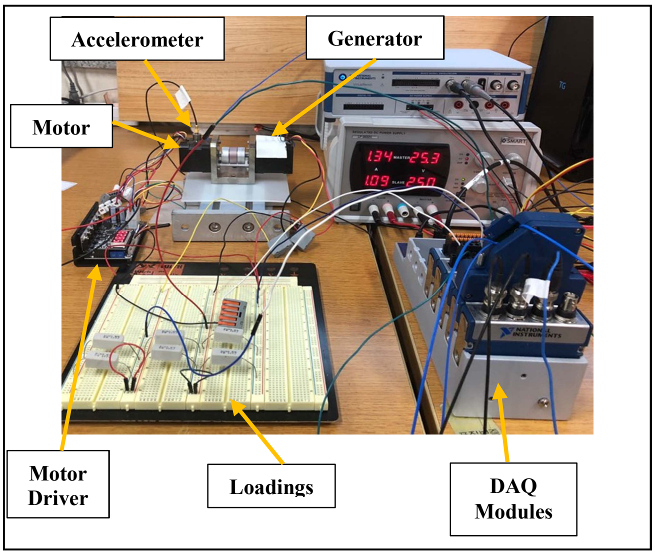

Fig. 2: Test Rig view for BLDC Motor test

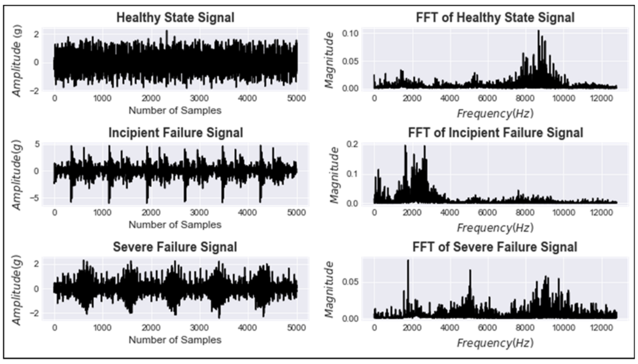

Fig. 3: Motor signals in different health states

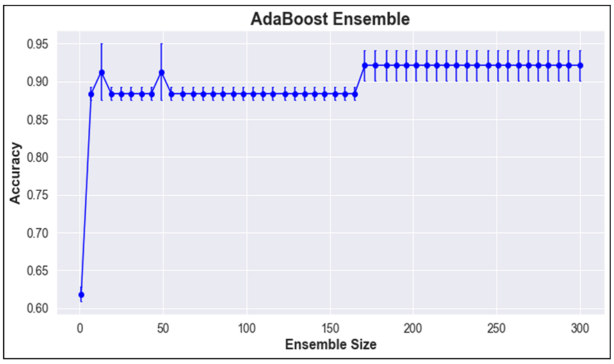

Fig. 4: Accuracy trend of AdaBoost technique

presence of several fault sidebands can be observed and as the fault propagates, sidebands also increase. Several CIs are extracted from time domain, frequency domain and time-frequency domain of motor lifecycle data. For a satisfactory SOH demonstration, one CI from time domain, kurtosis, and another CI from frequency domain, entropy is chosen for the classification. Kurtosis carries out the Gaussian normal distribution related information which is quite important since vibration of a system is random in nature. Higher kurtosis means the data has heavy tails or outliers which is undesirable. Another CI, entropy, is extracted from frequency domain and it indicates the disorientation of signal. Mathematical expressions of kurtosis and entropy are given in (6) and (7).

$$Kurtosis = \frac{N\sum_{n=1}^{N}[x(n)-\bar{x}]^4}{[\sum_{n=1}^{N}[x(n)-\bar{x}]^2]^2} \qquad (6)$$

$$Entropy = -\sum_{n=1}^{N}\frac{x(n)}{\sum_{k=1}^{N}X_k}\,log\,\frac{x(n)}{\sum_{k=1}^{N}X_k} \qquad (7)$$

Here,

$x(n)$ = Vibration signal in time domain

X_k = Vibration samples in frequency domain

N = Number of vibration samples

$\bar{x}$ = Mean of vibration samples

Both the features provide an intuitive notion to demonstrate vibration signal's gradual disorder, hence, estimating the SOH of motor [17].

IV. Result Analysis and Discussion

Random forest, being able to handle large datasets and higher dimensionality, provides a higher accuracy compared to many other machine learning algorithms. However, at the edge of decision boundaries, it fails to classify several features. To improve the accuracy of the RF classifier, AdaBoost is implemented where subsequent weak features are tweaked that were misclassified in previous RF classification.

In AdaBoost, as the number of estimators, **N**, increases, the accuracy also becomes better and better. Fig 4 shows the prediction accuracy with respect to ensemble size. However, a too large value of **N** will require a large amount of resources in order to perform computation. Therefore, we need to make a bias-variance trade-off in order to find an optimum value for **N**. As seen in Fig. 5 when **N**=1, the classifier fails to obtain a decision boundary for severe failure data. It classifies only the healthy and faulty class but, in the dataset, there are two types of faulty data. At **N**=1, RF classifier becomes essentially a binary classifier. For **N**=20, there is a decision boundary for all three classes, but, too many false predictions for test set data. **N**=200 gives a better result compared to previous ones

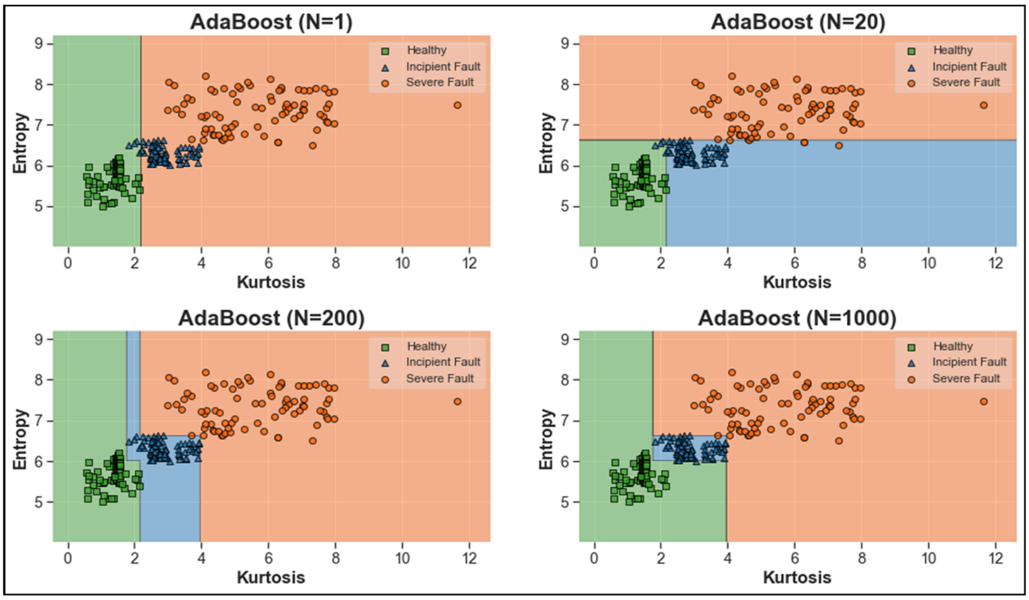

Fig. 5: Performance of AdaBoost algorithm for different number of estimators, **N**

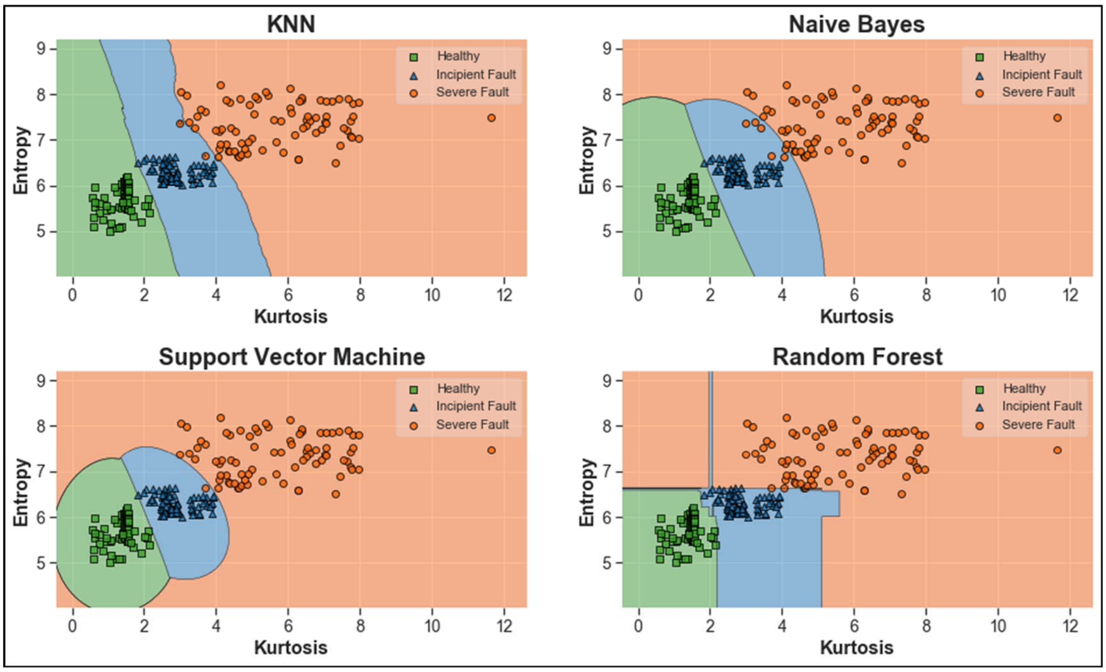

Fig. 6: Comparison among different classification techniques

with classification of all three classes and fewer mispredictions. When **N**=1000, RF classifier overfits the data causing poor predictions of the test set. In this scenario, classifier will be failed to predict a new set of data accurately. Besides overfitting, computational time and usage of resources also increase as **N** is increased. Approximately, it took 10 minutes when the classifier is trained with **N**=1000, around 5 minutes for **N**=200 and less than a minute for **N**=20,1. Therefore, choosing a proper value of **N** is important. For an optimum performance, that is by trading off accuracy and computational outflow, most favorable number of estimators should be set and for motor dataset, optimum value of **N** is selected as 200 for the boosting technique.

Fig. 6 illustrates a comparison among different classification algorithms. All the algorithms seem to be working quite well for motor data. However, the RF classifier boosted with AdaBoost is showing a better prediction yet not overfitting compared to other algorithms. SVM, KNN, and NB have a great accuracy except for a couple of misclassed data points at the edges of decision boundaries. KNN with neighbor size k=6 and Euclidean distance metric seem to perform well. Decision boundaries in KNN classification are quite well distributed which will be helpful for future predictions. NB classifier classified healthy and incipient failure data reasonably well but could not perform as well as KNN for severe failure data. Several severe failure data are classified within the incipient failure decision boundary.

SVM with a Gaussian radial basis kernel predicted the classes for all three SOH soundly. However, the decision boundaries are too much constrained for healthy and incipient failure data. This might cause overfitting for a new set of data. Finally, the RF classifier with boosting shows a somewhat better result compared to others. Decision boundaries and predicted test set data classified quite well, especially ate the edges of decision boundaries where other classifiers have some misclassifications. A comparison of achieved accuracy among these algorithms is presented in Fig. 7. Accuracy for KNN, NB, SVM, RF (boosted) is 94% (±0.01), 96% (±0.01), 95% (±0.01), 97% (±0.01), respectively.

The improvement of the RF classifier is due to the implementation of AdaBoost technique. How boosting improves the accuracy of RF classifier is shown in Fig. 8 where classification error for RF and RF with AdaBoost are plotted. It is seen that the classification error goes down as RF is boosted with AdaBoost. Since the dataset used in this

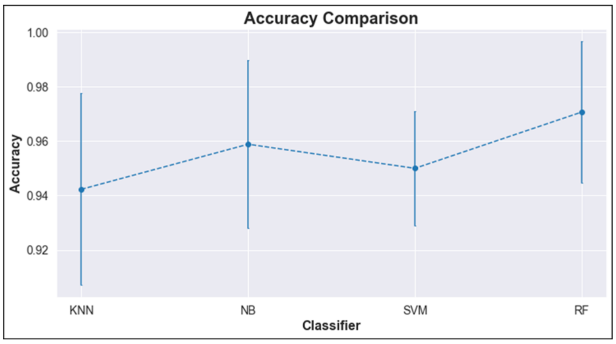

Fig. 7: Accuracy of different classification techniques

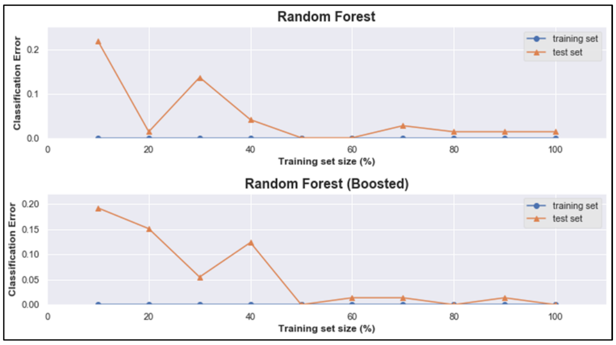

Fig. 8: Error trends of RF classifiers

study does not hold a large number of samples, the error observed is not too large. However, the intuition is clear from Fig. 8. After boosting, error rate declines as the number of training data increases. This is because each weak feature is retrained iteratively to achieve a better and better classification. Basically, the AdaBoost algorithm does not create any new strong feature combining some weak features, rather, it trains the weak features iteratively for a better approximation. Nevertheless, it makes the classifier stronger, providing some better predictions and decision boundaries in case of classification.

Besides having many advantages, AdaBoost has some disadvantages too, such as- it is too prone to be affected by outliers as it tries to fit each node perfectly. In that case, for noisy data, AdaBoost might not perform well. This can be referred more intuitively as the strength of weak learners. Some complex weak learners, particularly with noise, can lead to overfitting, hence, compromising the accuracy of the classifier. However, for a comparatively noiseless dataset, it performs quite well as seen from this study.

Stator related faults are some of the most frequent faults that occur in BLDC motors. This study focuses on the stator winding short-circuit that can lead to severe degradation in performance as well as cause a catastrophic failure of the system. For motor SOH estimation, vibration is one of the many attributes analyzed as it is proven that for almost any type of fault takes place in motor, there will be a change in its vibration. To further advance this study, these algorithms, particularly boosting will be further implemented for different types of motor faults such as- bearing related faults, rotor related faults, etc.

V. Future Works

In this study, AdaBoost is implemented with RF classifier only. In future, other classifiers such as SVM, KNN, NV will also be boosted using AdaBoost technique. Also, number features taken into considerations will also be increased by integrating more time and frequency domain features. The goal is to establish a proper fault classification technique for BLDC motors that can classify SOH accurately.

VI. Conclusion

In this study, an improved fault classification technique is presented for the fault diagnosis of an IPM type BLDC motor. Conventionally, binary classification techniques perform well for predicting two types of classes. In this study, three types of motor health data are presented from a BLDC motor's lifecycle data and classified using different classifiers. Random forest algorithm is emphasized due to its excellent performance with larger and higher dimension datasets. To improve the accuracy of RF classifier, it is boosted using AdaBoost and better classification results are observed for all three SOH of the motor. Parameter selection for boosting is quite an important aspect of AdaBooost technique. Computational resources and accuracy of classifier are kept in record for different parameter selections of AdaBoost, and the most suitable one is selected for classification purposes by trading off accuracy and computational expense. Accuracy and classification error trends for RF classifier with boosting and prior to boosting are also illustrated to have a better intuition about the effect of boosting on RF. Later, boosted RF classifier is compared with other classifiers such as- KNN, SVM, and NB. With default parameters, all the classifiers seem to perform quite well except for some minor misclassed features near to the decision boundaries. RF classifier, after boosted with AdaBoost, has a better classification compared to other techniques without boosting. However, since AdaBoost is too prone to overfitting, special care should be taken while choosing the optimum parameters such as- the number of estimators, learning rates, etc.

Vibration data acquired from a BLDC motor are used for the classification in this study. Since it is a permanent magnet synchronous machine (PMSM), these algorithms can be deployed for other similar types for PMSM rotary machinery too.

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