Smart Classifiers Based Classification and Condition Monitoring of Induction Motor Faults

Srinivas Chikkam, Sachin Singh, Rajvardhan Jigyasu, Amandeep Sharma

Abstract*: With the advancements in the field of automation in the industries the use of machines is very high and if the machine which require some rotatory action for the load, the Induction motor comes in to play because of the advantages such as robustness, low maintenance, low cost etc. But with the increase in the dependency over the motors it becomes highly recommended to have machines with reliability because break in the work can lead to huge amount of loss. In order to increase the reliability of the motors predictive maintenance comes into play which requires fault classification or detection which is easily and accurately possible using the Machine Learning algorithms. With the requirements of the present scenario for predictive maintenance, this paper presents the fault classification of induction motor using Support Vector Machine SVM) and K- Nearest Neighbour (KNN) technique of classification. Here in this paper the bearing fault (BF) and broken rotor bar (BRB) fault is considered. The results collected are on the basis of validation and Principle Component Analysis (PCA) technique. And it is found that the SVM technique is better than the KNN for fault classification of Induction motor.

***Keywords*: Induction Motor, Fault Diagnosis, Fault classification, SVM, KNN**

I. INTRODUCTION

The Fault classification and detection [1] is currently most favourite area of research now days because of its application. It helps in smooth working, increases efficiency, economical product [1, 2]. Induction motors (IM) now a day's became an important part of automation and are most noteworthy prime movers in industrial applications due to their simplicity, ruggedness and reliable construction [3]. IMs are extensively used in major sectors of industries, such as, railways, mining, wood working machines, automotive, chemical, paper mills, etc.

The commonly occurring faults in the Induction motor are bearing, broken rotor, shaft misalignment, stator short circuit faults and eccentricity faults [4]. The environmental and operating conditions are continuously decreasing the performance of Induction motor. Therefore diagnosis of faults in IM is essential prior to damage of motor to avoid production break down. Now a days with the advancements in the development approaches the predictive maintenance through Artificial Intelligence techniques known as condition monitoring which aims at predictive maintenance schedule depending upon the plant or process condition [5, 6]. The fault classification and diagnosis is first stage to achieve best condition based monitoring to increase the performance and efficiency of IM, enhancing life of IM, productivity, reducing internal and external losses [7]. The fault diagnosis and condition monitoring of induction motor become necessary to prevent the unpredicted breakdowns and reduce unscheduled downtime. The most important techniques for fault diagnosis are thermal monitoring, vibration monitoring, noise monitoring, torque monitoring and flux monitoring, current signature analysis [1]. There are many signal processing techniques which are very useful for fault detection purpose. These are classified as shown in Fig.1.

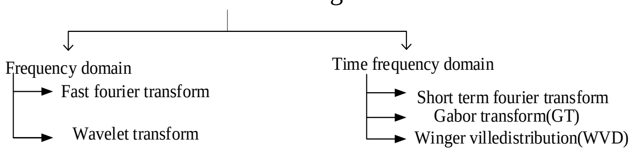

Fig.1. Classification of signal processing techniques

There are several fault Classification techniques are followed now a day's which are SVM [8,9], Artificial neural network [10,11], Fuzzy [12], KNN [13,14], Ensembles [15] and several more algorithms.

This section of the paper explains about the need of IM in the industries, different type of faults their detection and classification techniques, different signal processing techniques used in analysis as well as need of fault detection and diagnosis. Further this paper consists of following chapters, in chapter 2 techniques i.e. SVM and KNN than in chapter 3 experimental setup and features used, in chapter 4 results and discussion and in last conclusion.

II. TECHNIQUE USED

A. Support Vector Machine (SVM))

A support Vector Machine (SVM) is a major discriminative classifier well-defined by sorting out hyperplane. SVM is a non probabilistic binary classifier [16]. SVM forms a model that gives fresh data into one category or the other. Pattern recognition and classification, fault classification etc are basic functions which can be easily performed by the SVM classifier [17].

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Srinivas Chikkam, EEE Department, National Institute of Technology Delhi, Delhi, India. Email: srinivaschikkam@nitdelhi.ac.in

Sachin Singh, EEE Department, National Institute of Technology Delhi, Delhi, India. Email: sachinsingh@nitdelhi.ac.in

Rajvardhan Jigyasu, EEE Department, National Institute of Technology Delhi, Delhi, India. Email: rajvardhan@nitdelhi.ac.in

Amandeep Sharma, EE Department , National Institute of Technical Teacher Training and Research, Chandigarh, India, Email: engineer.amandeep@gmail.com

The optimization algorithm for linear SVM classification finds maximum margin hyper plane from given training data set A as defined as

A= $\left\{(\vec{u_i}, v_i) \mid \vec{u_i} \in i^p, v_i \in \{-1,1\}\right\}_{i=1}^{n}$ (1)

Where v_i is -1 or 1 and n is number of training data, each $\vec{u_i}$ is a p-dimensional vector having the feature quantity R.

SVM algorithm uses a set of different mathematical functions that are represented as kernel. The main function of kernels is to take data as input and transform it into required for selecting a kernel function is an important aspect for SVM based classification. Different algorithm uses different type of kernel functions. These functions are sigmoid, linear, nonlinear, polynomial and radial basis function (RBF). These kernel functions use for sequence data, text, graphs, images, text as well as vectors. Some kernel functions are as follows

The kernel functions of SVM are as follows

- Polynomial functions (For quadratic d=2; cubic d=3) is

$$k(u_i.u_j) = (u_i.u_j + 1)^d \quad (2)$$

- Gaussian kernels are

$$k(u,v) = \exp\left(\frac{-\|u-v\|^2}{2\sigma^2}\right) \quad (3)$$

- RBF or Gaussian function

$$k(u,v) = \exp\left(\frac{-\|u-v\|^2}{2\sigma^2}\right) \quad (4)$$

- Sigmoid functions

$$k(u,v) = \tanh(au^T v + c) \quad (5)$$

B. K-Nearest Neighbors

K-nearest neighbor classifier is capable to train the data and then identify its features. It allocates new array to the class among one of the classes of its k nearest neighbors, where k is an integer value which represents the number of nearest points considered [18]. The fig.2. explain the KNN classifier working. Here a testing point is displayed as a triangle surrounded by a number of training vector points (shown as squares and circles) for signifying two dissimilar classes. For K=1, the test point belongs to ‘class A’ because of least distance and if K=5, the test point belongs to ‘class B’ which is the majority class in 5 nearest points.

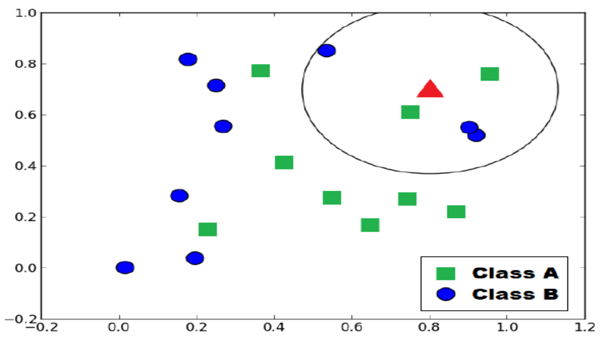

Fig.2. Example of KNN Classification

Minkowsky, Correlations, Manhattan, Chi-square and Euclidean distance [19] are the basic measurement algorithms which KNN follows for measuring distance between two points in feature space and are shown below by their mathematical expressions: -

Eulicidean (X,Y)= $\sqrt{\frac{\sum_{i=1}^{m}(u_i - v_i)^2}{m}}$ (6)

Minkowsky (X,Y)= $\left(\sum_{i=1}^{m}(u_i - v_i)^r\right)^{1/r}$ (7)

Correlation (X,Y)= $\frac{\sum_{i=1}^{m}(u_i - p_i)(v_i - p_i)}{\sqrt{\sum_{i=1}^{m}(u_i - p_i)^2 \sum_{i=1}^{m}(v_i - p_i)^2}}$ (8)

Mahalanobis (X,Y)= $\sqrt{(u-v)^T s^{-1}(u-v)}$ (9)

Hamming (X,Y)= $\sum_{i=1}^{m}|u_i - v_i|$ (10)

Here points X and Y are symbolized by the feature vectors X= $(u_1,u_2,u_3,\ldots\ldots\ldots u_m)$,B=$(v_1,v_2,v_3,\ldots.v_m)$, m represents dimensionality of the free space and S is the matrix for covariance.

C. Principle Component Analysis (PCA)

Mainly PCA is used to decrease the dimensionality of a data set containing of many variables connected with each other either deeply or lightly or used for increasing the correlation between the data sets. This techniques works on retaining the differences present in the data sets after modifications [20]. PCA converting the variables to a new set of variables, which are known as the principal, components are orthogonal to each other.

For dimensionality reduction

Let $X_1, X_2, \ldots\ldots X_M$ are $N \times 1$ vectors

Step1 :

$$\bar{x} = \frac{1}{M}\sum_{i=1}^{M} x_i \quad (11)$$

Step2: mean subtraction

$$\phi_i = x_i - \bar{x} \quad (12)$$

Step3: matrix formation

$$A=[\phi_1,\phi_2 .....\phi_M] \text{ (N} \times \text{ M matrix)} \quad (13)$$

Then compute,

$$C=\frac{1}{M}\sum_{n=1}^{M}\phi_n\phi_n^{T}=AA^T \quad (14)$$

Step4: compute the eigenvectors of

$$C: \lambda_1 \succ \lambda_2 \succ ....\lambda_N \quad (15)$$

Step5: compute the Eigen vectors of C:$u_1,u_2.....u_N$ since C is symmetric $u_1,u_2.....u_N$ form a basis i.e. any vector x or $(x-\bar{x})$ can be written as a linear combination of Eigen vectors.

$$(x-\bar{x}) = b_1u_1+b_2u_2+...b_Nu_N=\sum_{i=1}^{N}b_iu_i \quad (16)$$

Step6: (dimensionality reduction step) maintain only the terms corresponding to the K leading Eigen values i.e.

$$(x-\bar{x})=\sum_{i=1}^{N}b_iu_i \text{ Where } K \ll N \quad (17)$$

D. Validation Schemes

Cross-validation also known as rotation valuation or out-of-sample testing. In cross validation data set is randomly separated into k number of groups. These train and test set varies continuously until the test set becomes the train set like if there is a set 100 samples and 5 fold cross validation is applied than these 100 samples will get divided into 80 and 20 samples randomly for 5 times i.e. after one iteration previously which was test set will get included in the train set and from the train set of 80 samples one new 20 samples test set get generated in the last mean or average accuracy will be the result [21]. So it can be concluded that the cross-validation combines (averages) measures of fitness in prediction to obtain a more accurate estimation of model prediction performance.

Hold Out Validation scheme works on the principle that splits data into two datasets named as a 'train' and 'test' set. Here in this method after training, the testing is done using totally unseen data which helps a lot to get more accurate accuracy of trained model performance. Here in this method the selection of the testing set is in the percentage like if for validation 25% hold out scheme is selected and the data is of 100 samples than 25 data samples will be used to test or validate the model while the 75 samples will be used to train and both the data sets will be selected randomly.

III. EXPERIMENTAL SETUP

For collection of effective and accurate data a particular set up was designed. As shown in the Fig. 3[8], the system is combination of a 0.5hp 3-phase squirrel cage induction motor with 30 rotor bars, motor loading arrangement and National instruments (NI) based data acquisition system connected with computer. Data was obtained from the motor running under full load conditions and following fault conditions:

1. Healthy motor
2. Bearing fault- inner race defect
3. Bearing fault -outer race defect
4. 1-Broken rotor bar
5. 3-Broken rotor bars

Bearing defects shown in fig.4 (a) [8] were produced by creating holes (2mm diameter) on the inner and outer races of the ball bearings. The data was acquired from motor firstly in healthy condition, inner race defect, and outer race defect with faulty bearings at loading end of motor. Also, broken rotor bar faults shown in fig.4(b) [13] were created by drilling holes of 6mm diameter on the rotor, so that the bar is completely removed. The current signal was acquired from motor with 1 and 3 broken rotor bars. The motor shaft, at full load was rotating at about 20-24 Hz. The current signal was acquired from motor using an NI based data acquisition system.

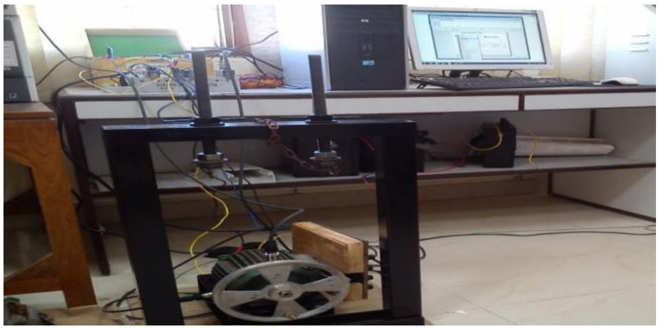

Fig.3. Experimental Setup

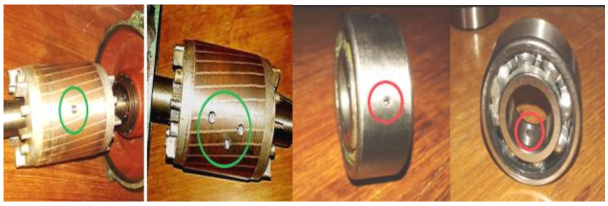

Fig.4. (a) Rotor with 1-BRB and 3-BRB; (b) Outer race and Inner race defect

A. Signal Processing and Feature Extraction

The steps followed for extraction of meaningful features for classification of bearing fault, broken rotor bar and healthy states of motor are shown in Fig. 5 below. A single phase currents (i_a) is measured from the motor and is squared to compute signal power. Bearing fault is a mechanical fault, thus it is anticipated that the power of current signal is more sensitive to presence of faults rather than the signal itself. Thus, the signal power is computed before segmentation and feature extraction.

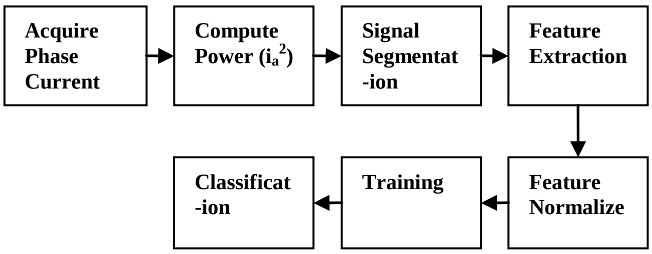

Fig.5. Block diagram of proposed methodology

After computing the power signal, the signal was segmented into overlapping segments and 20 segments were obtained. Here, each segment contained at least 8000 samples, corresponding to 9 to 10 revolutions of motor shaft.

For each segment, the following time domain features were extracted: mean, variance, kurtosis, skewness, crest factor, shape factor, impact factor, margin factor, median, range. For acquisition of universal model after feature extraction the obtained features were normalized before giving them for training. Except the skewness all the features were normalized in the range of [0, 1] while skewness normalized in the range of -1 to 1. The training is performed using holdout validation and cross validation to optimize the classifier performance. After training, the classifier is tested with the unseen data to obtain the classification accuracy.

IV. RESULTS AND DISCUSSION

In this paper power signal i.e. current square signal is used for the analysis from which the features are extracted and used to train the models with different validation schemes. The results shows the different accuracies obtain while training which is basically a measure of how good the classification training has been done and how good it could be able to classify the faults which are bearing and rotor faults from the healthy one.

A. Using SVM Technique

Support vector machine works on the principle of maximum support distance between the two parallel vector which ensures the presence of maximum classification rate. It is basically classifying linear and nonlinear data, clarification with linear data is quite easy but for the nonlinear data classification it uses kernel functions. There are different kinds of kernel function available in the SVM classifier which follows different classification approaches and shows good classification results only if the data used for training satisfies the set of parameters. Like if the date present is of linear in nature it can be classified with the linear kernel function and will give maximum classification accuracy. In this paper the default values of the classifier parameters were considered which are box constraint kept 1, kernel scale kept auto for linear, quadratic and cubic SVM method and for fine Gaussian 0.83, medium Gaussian 3.3 and coarse Gaussian it is kept 13 and multi class method was kept One to One for all SVM's. Table 1, Table 2 and Table 3 shows various results obtained using the classifier SVM on different validation schemes and with and without PCA for accuracies of the classifier. From the results it is clear that when we use cross validation schemes with 5 fold the overall accuracy obtained of without PCA is 99.5% which is better than using PCA but in case of Holdout validation with 25 % holding the data i.e. out of 100, 25 samples were used for validation and 75 used for training of the classifier the accuracy obtained with PCA along with all 11 features found 88.66% which is better than the without PCA technique. From table 3 of our results the accuracy obtained is maximum i.e 100% and there is no effect of the PCA over the results but here the time taken during the training and validation was found more than the cross and hold out validation.

Table- I: Accuracies Obtained Using Svm Classifier On Different Kernel Functions Without Pca, With Pca And Pca With All Features With 5 Fold Cross Validation

S.No	Type	Accuracy(%)			
		Without PCA	*With PCA*		Total
			Specified Variance	*Specified Components*	
1	Linear	100	100	98	99.3
2	Quadratic	100	100	98	99.3
3	Cubic	100	100	99	99.6
4	Fine Gaussian	98	98	68	88
5	Medium Gaussian	99	100	99	99.6
6	Coarse Gaussian	100	84	99	94.3
Total		**99.5**	97	93.5	

Table –Ii: Accuracies Obtained Using Svm Classifier On Different Kernel Functions Without Pca, With Pca And Pca With All Features

S.No	Type	Accuracy(%)			
		Without PCA	*With PCA*		Total
			Specified variance	*Specified components*	
1	Linear	64	44	96	68
2	Quadratic	76	60	100	78.66
3	Cubic	76	48	100	74.66
4	Fine Gaussian	60	48	52	53.33
5	Medium Gaussian	56	52	96	68
6	Coarse Gaussian	60	40	88	62.66
Total		65.33	48.66	**88.66**	

Table- Iii: Accuracies Obtained Using Svm Classifier On Different Kernel Functions Without Pca, With Pca And Pca With All Features With No Validation

S.No	Type	Accuracy (%)			
		Without PCA	*With PCA*		Total
			Specified Variance	*Specified Components*	
1	Linear	100	100	100	100
2	Quadratic	100	100	100	100
3	Cubic	100	100	100	100
4	Fine Gaussian	100	100	100	100
5	Medium Gaussian	100	100	100	100
6	Coarse Gaussian	100	100	100	100
Total		**100**	**100**	**100**	

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Figure 6 shows overall comparison of different validation schemes i.e. cross, hold and no Validation along with the accuracies with and without PCA. From figure it is clear that overall accuracy for the no validation is higher than the other schemes which are 100% with and without PCA dependency.

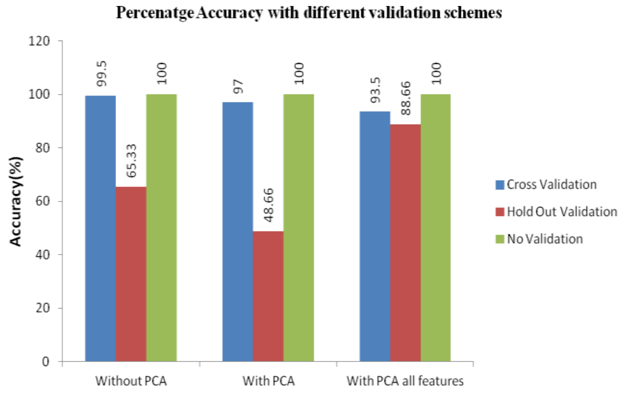

Fig.6. Percentage accuracy for SVM classifier with different validation schemes

B. Using KNN Technique

The K-Nearest Neighbor classification technique has advantages such there is no training phase, robustness to noisy training data, and ease to learn complex models. Though K-NN also suffers from the problem of selection of best K value as well as appropriate distance matrices. For classification of unknown new feature vector, the KNN follows non-parametric approach, where computation is performed online. The KNN classification techniques is mainly classified the basis of number of nearest neighbors and distance metrics like medium, cosine, cubic and weighted works with nearest neighbor value of 10 while fine on 1 and coarse on 100. The Fine, medium, coarse and weighted KNN works with Euclidean distance metric while cosine works with cosine and cubic with minkowski. All these KNN techniques have equal distance weights except weighted KNN which have squared inverse type. The results are calculated with cross, holdout and no validation with and without PCA. From table 4, 5, 6 the results are shown. The table 4 shows the results of accuracy along with the cross validation with 5 folds and the overall accuracy obtained by the without PCA i.e. 84.66% is highest than the other techniques but when we go with the individual classifier the techniques achieved 100% accuracies which is better than the overall accuracy. The table 5 shows results for the Hold out validation schemes with 25% data holding i.e. out of 20 samples from each category 5 are kept for validation while 15 for training and testing, it is found that the overall accuracy obtained by the with PCA scheme and for all features considered is found to be best i.e. 82%. The Table 6 shows the results obtained without any validation i.e. all 100 samples are used for training and testing only there in no validation the classification with and without PCA nearly performed same and achieved 100% for different classifications but the overall accuracy of the without PCA found to be more i.e. 86%.

Table- Iv: Accuracies Obtained Using Knn Classifier Without Pca, With Pca And Pca With All Features With 5 Fold Cross Validation

S.No.	Type	Accuracy (%)			
		Without PCA	*With PCA*		Total
			Specified Variance	*Specified Components*	
1	Fine	100	100	100	100
2	Medium	100	100	95	98.33
3	Coarse	20	20	20	20
4	Cosine	100	86	98	94.66
5	Cubic	96	100	93	96.33
6	Weighed	100	100	100	100
Total		86	84.33	**84.33**	

Table –V: Accuracies Obtained Using Knn Classifier Without Pca, With Pca And Pca With All Features With 25% Holdout Validation

S.No	Type	Accuracy(%)			
		Without PCA	*With PCA*		Total
			Specified Variance	*Specified Component s*	
1	Fine	56	56	92	68
2	Medium	44	40	96	60
3	Coarse	20	20	20	20
4	Cosine	52	44	96	64
5	Cubic	48	44	92	61.33
6	Weighed	60	56	96	70.66
Total		46.5	43.33	82	

Table -Vi: Accuracies Obtained Using Knn Classifier Without Pca, With Pca And Pca With All Features With No Validation

S.No	Type	Accuracy (%)			
		Without PCA	*With PCA*		Total
			Specified Variance	*Specified Components*	
1	Fine	98	100	98	98.66
2	Medium	98	100	84	94
3	Coarse	20	20	20	20
4	Cosine	97	80	94	90.33
5	Cubic	96	100	83	93
6	Weighed	99	100	93	97.33
Total		84.66	83.33	78.66	

Figure 7 shows overall comparison of different validation schemes i.e. cross, hold and no Validation along with the accuracies with and without PCA. From figure it is clear that overall accuracy for the no validation without PCA is higher than the other scheme which is 86% while on the second place the accuracy of cross validation without PCA is 84.66%.

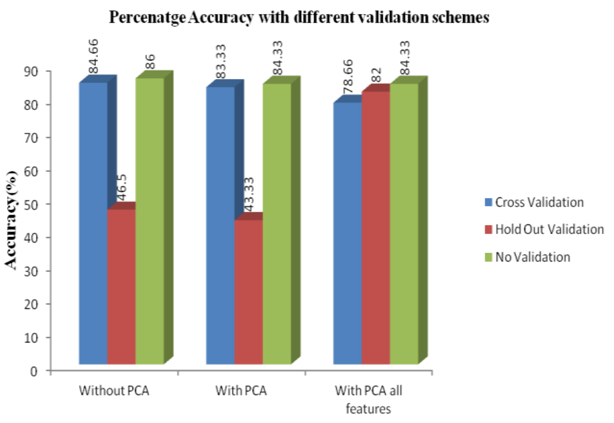

Fig.7. Percentage accuracy for KNN classifier with different validation schemes

V. CONCLUSION

In this paper, a novel and simple method is proposed to identify bearing and broken rotor bar faults of induction motor, by using simple time domain features obtained from power signal of motor current. Normally, it is observed that the MCSA of motor faults is difficult as compared to vibration based diagnostics. However, the proposed method uses the squared current (power) signal to obtain time domain features, which shows acceptable high classification accuracy. In this paper two majorly used techniques which are SVM and KNN are used to classify the faults.

This paper proposed the model for classification of bearing and broken rotor bar fault using SVM and KNN classifier and their results has been calculated on the basis of their classification accuracy generated during the different validation techniques and along with and without PCA. From the results it has found that the Classification over the acquired data achieved 100% overall accuracy during the no validation in SVM classification technique in which there is no effect of PCA over the results, this classification accuracy is better than the overall accuracy obtained by the KNN classifier. Among all the classifiers of SVM, the cubic 91.44% and medium 89.22% classifier performed best. In KNN, Fine KNN 88.88% and weighted KNN 89.33% performed best among other classifiers of KNN. In the last it can have concluded that individually as well as combinedly the SVM classification model performed best than the other techniques with the No validation case, also it is found that the accuracy obtained during the classifier shows that the results get vary in every model run so average of multiple runs of model for better accuracy results should be considered. Also PCA never gives best results every time it totally depends over the data over which the training testing and validation has to be done.

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AUTHORS PROFILE

Srinivas Chikkam received BE in Electrical and Electronics Engineering from SRKR Engineering college in Bhimavaram, MTECH in Power Electronics From JNTU Kakinada. He is currently pursuing PhD from National institute of Technology, Delhi. He is life member of Institute of Engineers India (MIE). His area of interest is Machinery condition monitoring, signal processing and Induction motor drives.

Dr Sachin Singh received his B.tech in Electrical and Electronics Engineering from B.I.T Meerut, India in 2007. M.Tech in Solid State Electronics Materials from Indian Institute of Technology, Roorkee, Uttarakhand, India in 2010. He has completed his PhD in the Department of Electrical Engineering, Indian Institute of Technology, Roorkee Uttarakhand, India. He is currently working as Assistant professor in the Department of Electrical and Electronics Engineering, National institute of Technology, Delhi. His fields of interest are condition monitoring of Induction Motor, signal processing, speech enhancement, speech recognition and biomedical instrumentation.

Rajvardhan Jigyasu born in Lucknow (Uttar Pradesh). He received his B.Tech in Electrical and Electronics from Shri Ramswaroop Memorial Group Of Professional Colleges (SRMGPC), Lucknow, Uttar Pradesh in 2014 and M.E. in Instrumentation and control Engineering from Electrical Engineering Department, National Institute of Technical Teacher Training and Research (NITTTR) affiliated to Punjab University, Chandigarh. He served for one year (2015-2016) as Lecturer in Dr. M.C. Saxena Group Of Colleges, Lucknow Uttar Pradesh (U.P) and one year (2018-2019) as Assistant Professor in Shri Ramswaroop Memorial Group Of Professional Colleges (SRMGPC), Lucknow, Uttar Pradesh. He is currently pursuing Ph.D. from NIT, Delhi. He has published several research papers and articles in reputed journals and Conferences. His current research interests includes electrical machines, power system analysis and artificial intelligence and machine learning algorithms.

Amandeep Sharma was born in Chandigarh, India on 19 August 1984. He received his B.E. in Electronics and Communication Engineering from University Institute of Engineering and Technology (UIET), Panjab University, Chandigarh in 2007 and M.Tech. degree in Instrumentation from University Centre for Instrumentation and Microelectronics (UCIM), Panjab University, Chandigarh, India in 2009.He worked as a Junior Research Fellow (JRF) in Central Scientific Instruments Organization (CSIO), Chandigarh working under DST funded project from September 2009 to May 2011. He served for about two years as Assistant Professor, Instrumentation and Control Engineering (ICE) Department of Dr. B. R. Ambedkar National Institute of Engineering and Technology Jalandhar, Punjab, India from August 2011 to October 2013. Presently, he is pursuing his Ph.D. from the Electrical Engineering Department, National Institute of Technical Teachers Training and Research (NITTTR), Panjab University, Chandigarh in the area of condition monitoring of electrical motors. His research interests include condition monitoring of electrical machines using statistical methods and machine learning algorithms, artificial intelligence-based computation and multi-agent classifier systems. He is particularly interested in the analysis of non-stationary signals and model-based fault diagnosis. Mr. Amandeep Sharma is a Life Member of Indian Micro-electronics Society, IMS (India).