Vibration Signature Analysis using Rough Sets and Analogy-Based Reasoning Classification

Chhaya Grover, Neelam Turk

***Abstract**: Various machine learning techniques along with vibration signal processing techniques are being explored for effective and accurate fault diagnosis of bearing faults. This work studies and evaluates the application of rough set based algorithms - RoughSet Classifier, LocalKnn Classifier and RseslibKnn Classifier and their combinations with 4 kinds of distance metrics - City block and Hamming (CBD and HD), City block and simple value difference (CB and VDM), Density based value difference (DBVDM), Interpolated value difference(IVDM) for bearing vibration signature analysis. The input vector fed to the classifier models is composed of statistical features extracted from pre-processed vibration signals. The different metrics used to compare the performance of the classifiers show that RseslibKnn classifier with City block and simple value difference distance metric takes considerably less time for training (9.09 sec) and classification (0.86 sec) while giving testing accuracy of 84.1442 %, thereby confirming its usefulness for real time application on large bearing fault datasets. The results obtained in this paper show the effectiveness of rough sets based algorithms, particularly KNN based classifiers, in bearing fault diagnosis.*

Keywords: Vibration signature analysis, Rough set based classifiers, Intrinsic Mode Functions, Empirical mode decomposition.

I. INTRODUCTION

Bearings are an important part of many machines, as they reduce friction between moving parts, allowing them to move smoothly without inducing stress. Bearing are required to support various kinds of forces like axial, radial or bending moments. They operate under high speed and high load conditions and wear out over time. Regular monitoring and maintenance of bearing is critical for maintaining safety standards and fault free operations of the industrial machines. Depending upon their use bearings can be of different types e.g. plain bearing, rolling element bearing, fluid bearing, magnetic bearing. Rolling-element bearings are widely used in the industries today. The major parts of a rolling element bearing are inner and outer race, balls, and cage. The rolling-element bearings develop faults in the outer race, inner race and ball due to metal-to-metal contact.

To prevent premature failure, bearing conditions are monitored regularly through its vibration signature analysis. Vibration signals are picked up through accelerometers installed at appropriate positions in the machines. They are pre-processed and suitable features are extracted from them to create a dataset. Researchers have used many types of machine learning and deep learning classifiers to analyze and classify these feature data sets. In literature k-nearest neighbour classifier and its variants have been explored by researchers. Q. Wang et. al. applied a combination of Kernel Principal Component Analysis and K-Nearest Neighbour for bearing fault diagnosis.[1]. In the first step they used the feature vector of the Kernel Principal Component Analysis, and in second step the sensitive features were input to K-Nearest Neighbour classifier. A comparison of KNN and artificial neural network was done by A. Moosavian et. al. for fault diagnosis of a journal-bearing of IC engine [2]. They extracted 30 frequency domain features from the PSD values of the vibration signals to train KNN and ANN and concluded that KNN needs less time for training as compared to ANN while accuracy of ANN is better. R. Gunerkar, A. Jalan and S. Belgamwar used wavelet transform for denoising the vibration signal and extracted five features from the signal. The dataset obtained is used to train ANN and KNN for bearing fault classification [3].

S. Mehta et. al. proposed a local mean based k-harmonic nearest centroid neighbour classifier. They combined proximity based on distance metrics along with spatial distribution of k neighbours. The k nearest centroid neighbours in each class were computed and used to find k different local mean vectors, and then utilized to compute their harmonic mean distance to the sample. The sample is assigned to the class with minimum harmonic mean distance. [4] A. Sharma et. al. proposed a weighted K nearest neighbour Classifier which used a squared inverse feature weighting technique to improve the performance of k-nearest neighbour classifier. They experimentally verified the effectiveness of weighted-KNN Classifier using different distance metrics and different number of nearest neighbours.[5]

Researchers have explored the use of rough set theory and analogy based reasoning for classification algorithms[6][7]. In machine learning, Analogy-based reasoning methods allow us to reason out and take decision about objects based on the similarities between them. Using analogy-based reasoning paradigm, A. Wojna modified distance metrics and used them to develop improved k-nearest neighbour classifiers.[7]

Manuscript received on February 10, 2020.
Revised Manuscript received on February 20, 2020.
Manuscript published on March 30, 2020.
* Correspondence Author
Chhaya Grover*, Department of Electronics Engineering, J.C. Bose University of Science and Technology, YMCA, Faridabad, India. E-mail: chhayagrover@jssaten.ac.in
Dr. Neelam Turk, J.C. Bose University of Science and Technology, YMCA, Faridabad, India.

Rule based and k-nearest neighbours classification algorithms based on rough set theory have been developed. C. Xin et. al. performed bearing fault diagnosis by Kurtosis computation in time-domain and wavelet analysis in frequency domain. The fault diagnosis algorithm was built by attribute reduction based on rough set .[8]

X. Zhu, Y. Zhang and Y. Zhu used statistical features and combined the kernel method and neighborhood rough sets to design the wrapper feature selection algorithm in their proposed methodology of bearing fault diagnosis [9]. J. Yan et. al. reduced the fault data of rolling bearing by the application of greedy algorithm of rough set and used neural network for classification [10]. V. Muralidharan and V. Sugumaran used wavelet features with rough set and fuzzy logic for fault diagnosis of centrifugal pumps using vibration signals. Rules were generated by applying Rough set theory and the faults are identified based on the strength of the rules [11]. W. Li, W. Pan and S. Zhang proposed a rough set and back propagation neural network based algorithm for rolling bearings fault diagnosis. It was seen that rough set was able to reduce the dimensionality of the raw feature set and rough sets combined with BP neural network effectively classified bearing faults[12].

In this work three classifiers based on rough set theory are explored for rolling element bearing fault diagnosis. One classifier is rule based classifier and two classifiers are k-nearest neighbour based classifiers. First Vibration signals are processed using Empirical Mode Decomposition (EMD) [13], then best Intrinsic mode function (IMF) was selected and seven statistical features are extracted from all best IMFs. The feature dataset was divided between training and test datasets. Rough set based classifiers are first trained using training dataset and then test dataset is applied to compute test classification accuracy.

II. ROUGH SET BASED CLASSIFIERS

The Rough set is composed of two crisp sets, out of which one represents the lower boundary and second represents the upper boundary of target set. Following three classification algorithms based on rough set theory are used in this study:

A. RoughSet Classifier

This is a rule based classifier whose rule induction is based on rough sets theory. Its classification algorithm is based on the principles of discernibility matrix, reducts and rules generated from reducts. A discretization method (e.g. equal width, equal frequency static or dynamic entropy minimization), a type of discernibility matrix and an algorithm generating reducts (e.g. local/global and all/partial) is selected and then the classifier computes a set of decision rules. If “O” is the object to be classified, then the classifier calculates the vote of each decision class and the decision with the greatest vote is assigned to “O”

$$vote_i(O) = \sum_{(q \to (s1, s2 \ldots, sm)) \in Rules:\, O \text{ matches } q} s_i \, . \, support\left(q \to (s1, s2 \ldots, sm)\right)$$

The decision with greatest vote is assigned to the object “O” [14] [15]

B. LocalKnn Classifier

The second classifier LocalKnn is the extended version of the KNN classifier that utilizes local metric induction for each classified object. It applies a global metric to find a large set of neighbours and then generates a local metric to select k nearest neighbours. Then it generates a new, local metric from this large set of neighbours. This selected k nearest neighbours are used to vote for the decision. It can handle large data sets reasonably well and improves accuracy if data contains nominal attributes. [14] [15]

C. RseslibKnn Classifier

This is a modified K nearest neighbours classifier that provides variety of distance measures and has built-in feature to compute optimal value of k. It can classify large datasets because of its very fast neighbours search algorithm. In the learning phase a distance measure is induced from a training set and an indexing tree is built to achieve fast neighbour search. The algorithm can also learn the optimal value of k from the training set. The classifier provides two distance metrics for nominal attributes: Hamming distance(HD) and Value Difference Metric (VDM). There are three metrics for numerical attributes: The City-block distance (CBD), Density-Based Value(DBVDM) and Interpolated Value Difference Metric (IVDM). Weights computation in the distance measure is done by three methods: a method using perceptron, method based on distance and methods based on accuracy.

The classifier applies induced distance measure to find k nearest neighbours in the training set and it applies one of three methods of voting (equally weighted, with inverse square distance weights or with inverse distance weights) for the decision by the neighbours. [14] [15]

III. MATERIALS AND METHODS

The ball bearing dataset for the experiments was downloaded from Case western university’s website.[16] This data was generated by a test bench having Reliance Electric motor of 2HP, a dynamometer, a transducer/encoder and accelerometers for capturing vibration signals. The specification of the bearing and various parameters for data collection are shown in the Table-I

Vibration signals are decomposed using empirical mode decomposition. This pre-processing step resulted in various intrinsic mode functions and residue. The correlation coefficient of IMFs with respect to original signal is calculated and the IMF with highest correlation coefficient is selected for further processing. Rest all IMFs and residue are discarded.

From the selected IMF seven features: Mean, RMS, Standard Deviation, Median, Skewness, Kurtosis and Crest factor are calculated. These features are given in Table-II.

Mean and RMS value of vibration signal will increase progressively with the fault development in bearing. Variance quantifies the spread or dispersion of vibration signal around its mean. Skewness gives a measure of the asymmetry of probability density function of vibration signal. Kurtosis measures the degree of flatness of the probability density function near its center.

The kurtosis value of normal bearing normal remains at 3 and deviates in case of bearing fault. Crest Factor is defined as maximum value of a vibration signal divided by its RMS value. Crest factor is a measure of impact during rolling element and inner/ outer raceway contact.

Table-I: Bearing dataset specifications

Bearing specification							
Position	**Number**	**Type**	**Inside Diameter**	**Outside Diameter**	**Thickness**	**Ball Diameter**	**Pitch Diameter**
Drive end bearing	6205-2RS JEM SKF	deep groove ball bearing	0.9843 inch	2.0472 inch	0.5906 inch	0.3126 inch	1.537 inch
Fan end bearing	6203-2RS JEM SKF	deep groove ball bearing	0.6693 inch	1.5748 inch	0.4724 inch	0.2656 inch	1.122 inch
Sampling Frequency							
Drive end	12000 samples / sec and 48000 samples / sec						
Fan end	48000 samples / sec						
Motor Speed							
1797 RPM, 1772 RPM, 1750 RPM, 1730 RPM							
Motor Load							
0 HP, 1 HP, 2 HP, 3 HP							
Fault Types							
Inner Race, Outer Race, Ball Bearing							
Fault Size Diameter							
0.007 inch, 0.014 inch, 0.021 inch, 0.028 inch							
Data Files Used							
Training	13647						
Test	3411						

Table-II: Description of Statistical Features

Feature	**Formula**	**Notations**
Mean	$\frac{1}{N}\sum_{n=1}^{N}\lvert x(n)\rvert$	x(n): Sampled vibration signal N: No. of samples µ: mean σ : Standard deviation
RMS	$\sqrt{\frac{1}{N}\sum_{n=1}^{N}x^2(n)}$	
Standard deviation	$\sigma=\sqrt{\frac{1}{N-1}\sum_{n=1}^{N}[x(n)-\mu]^2}$	
Median	$\left[\frac{50(N+1)}{100}\right]^{th}$ observation	
Skewness	$\frac{\sum_{n=1}^{N}[x(n)-\mu]^3}{(N-1)\sigma^3}$	
Kurtosis	$\frac{\sum_{n=1}^{N}[x(n)-\mu]^4}{(N-1)\sigma^4}$	
Crest factor	$\frac{\max\lvert x(n)\rvert}{\sqrt{\frac{\sum_{n=1}^{N}x^2(n)}{N}}}$	

The feature vector is created by extracting these seven features from all of the signals in the dataset. The feature dataset is further split in 80%-20% ratio to generate training and test datasets. The three classifiers are trained using training dataset and trained models are used to classify test data set. The metric values for all classifiers are tabulated in Table-IV and Table-V.

Parameters for three classifiers used in this study are discussed below:

Rough set rule based classifier

All local method is chosen as Reducts generating method. Ordinary decision and consistencies omitted criteria is used to build Discernibility matrix. Local maximal discernibility heuristic is used to discretize numerical attributes

LocalKnn Classifier

This classifier is designed to improve accuracy as compared to the standard kNN. The classifier is set to learn the optimal value of k i.e. number of nearest neighbours. Hence the value of k used to vote for decision is set automatically. Inverse square distance voting is used for the decision making by nearest neighbours

RseslibKnn Classifier

It is capable of implementing fast neighbour search in large data sets by using indexing to accelerate the search of nearest neighbours. The classifier is set to learn the optimal number of nearest neighbours for efficient classification. by giving vote for decision. Type of voting used is based on inverse square distance. The equation for common distance metric for KNN based classifiers is defined as below in Table-III

Table-III: Distance Metrics

$d_{ij} = \left[\sum_{i=1}^{n} \lvert x_{ik} - x_{jk}\rvert^{p}\right]^{\frac{1}{p}}$	p=1	p=1, binary data	p=2
k: index of coordinates	City Block distance	Hamming distance	Euclidean distance

The simple value difference, density based value difference and interpolated value difference as discussed by are used in conjunction with these.[17] [7]

IV. RESULTS

Bearing vibration signals obtained from normal and faulty bearings are pre-processed before feature extraction as discussed above. The statistical spread of all features is shown in Fig.1. The extracted feature set is used to train the three rough set based classifiers and their performance is compared on the basis of Training time, Classification time, Testing Accuracy, Kappa statistics, Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics are shown in Table-IV.Further comparison on the basis of Precision and Recall and area under their curves, True and False positive rates, F-measure and Matthews correlation coefficient are shown in Table-V. These comparisons are graphically shown as bar diagrams in Fig.2, Fig.3., Fig.4. and Fig. 5. We also compared LocalKnn and RseslibKnn on the basis of different distance metrics in the KNN classification model. The best classification accuracy is given by LocalKnn with City Block and VDM distance metrics.

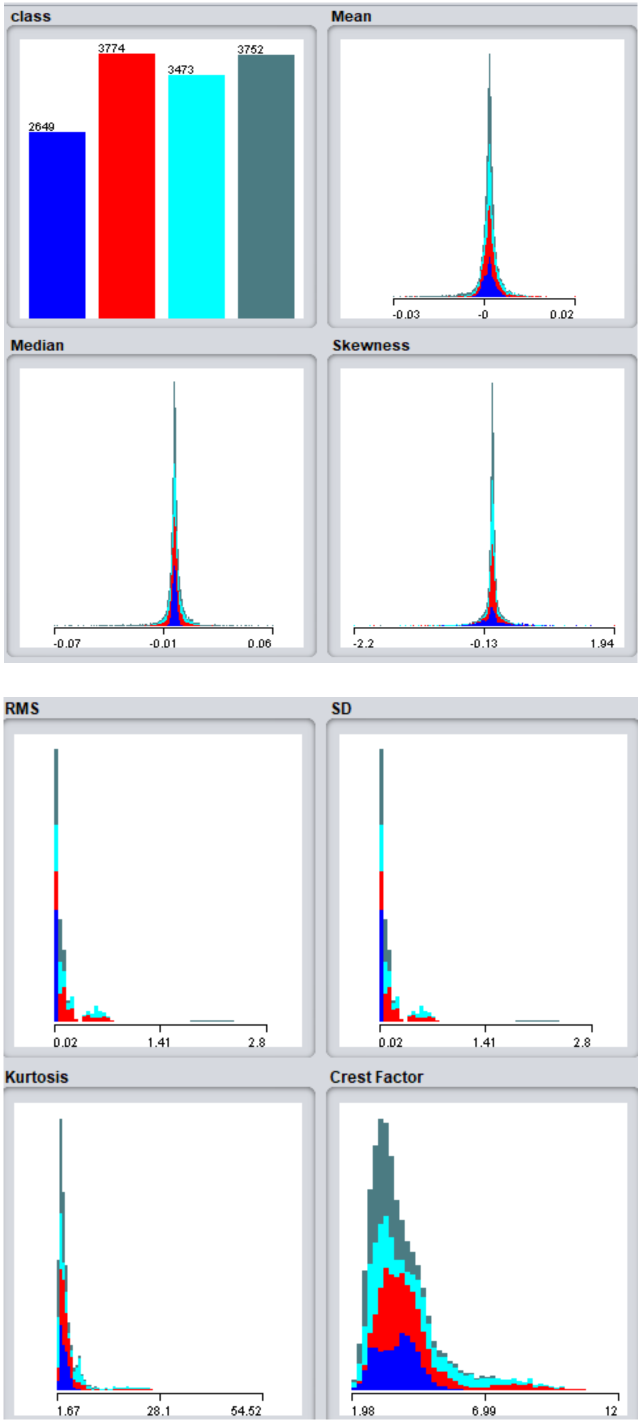

Fig.1. Visualization of Features with respect to four classes

Table-IV: Classifier Comparison Metrics

Classifier / Metric		Optimal value of K	Training Time	Classification Time	Testing Accuracy	Kappa statistic	Mean absolute error	Root mean square error
Rough Set			38.67	137.37	68.82%	0.5854	0.1552	0.394
	City block & Hamming	K=10	250.08	252.21	84.67%	0.7946	0.0766	0.2768

	City block & simple value difference	K=13	258.61	251.92	**85.52%**	**0.806**	**0.0724**	**0.2691**
	Density based value difference	K=11	420.04	391.49	84.29%	0.7893	0.0785	0.2803
LocalKnn	Interpolated value difference	K=14	411.45	377.45	85.14%	0.8008	0.0743	0.2726
	City block & Hamming	K=13	9.78	0.99	84.06%	0.7866	0.0797	0.2823
	City block & simple value difference	K=15	**9.09**	**0.86**	84.14%	0.7878	0.0793	0.2816
	Density based value difference	K=15	34.59	9.53	81.59%	0.7534	0.092	0.3034
RseslibKnn	Interpolated value difference	K=22	31.14	3.17	84.73%	0.7956	0.0763	0.2763

Table V: Classifier Comparison Metrics Contd.

Classifier	Metric	True Positive Rate	False Positive Rate	Precision	Recall	F-Measure	Matthews correlation coefficient	Area under recall curve	Area Under precision curve
Rough Set		0.69	0.104	0.69	0.69	0.687	0.582	0.792	0.557
LocalKnn	City block & Hamming	0.847	0.052	0.847	0.847	0.846	0.794	0.897	0.758
	City block & simple value difference	**0.855**	**0.049**	**0.856**	**0.855**	**0.855**	**0.805**	**0.903**	**0.77**
	Density based value difference	0.843	0.054	0.843	0.843	0.842	0.788	0.895	0.752
	Interpolated value difference	0.851	0.05	0.852	0.851	0.851	0.8	0.901	0.764
RseslibKnn	City block & Hamming	0.841	0.53	0.842	0.841	0.84	0.786	0.894	0.75
	City block & simple value difference	0.841	0.053	0.843	0.841	0.841	0.787	0.894	0.751
	Density based value difference	0.816	0.062	0.818	0.816	0.815	0.753	0.877	0.715
	Interpolated value difference	0.847	0.051	0.849	0.847	0.847	0.795	0.898	0.759

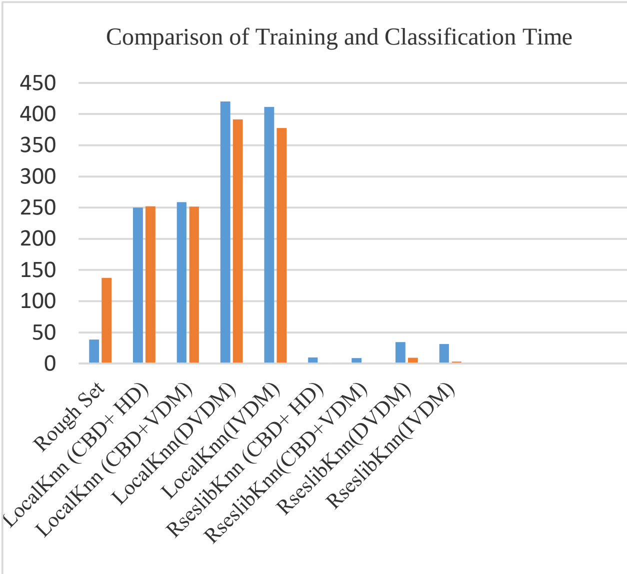

Fig.2. Comparison of training and classification time for classifiers

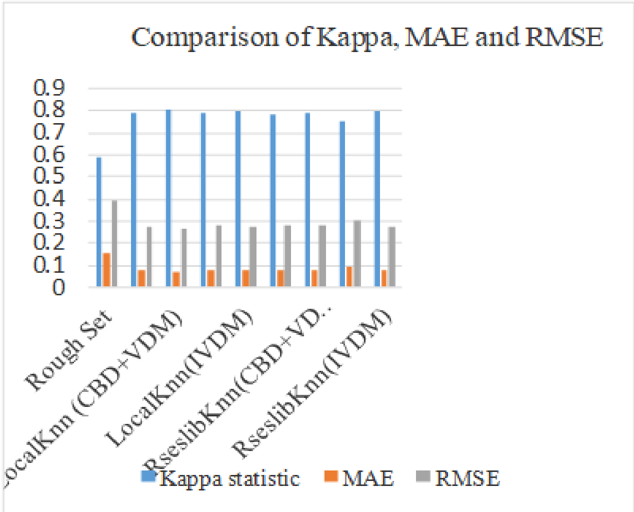

Fig.4. Comparison of Kappa, MAE and RMSE for classifiers

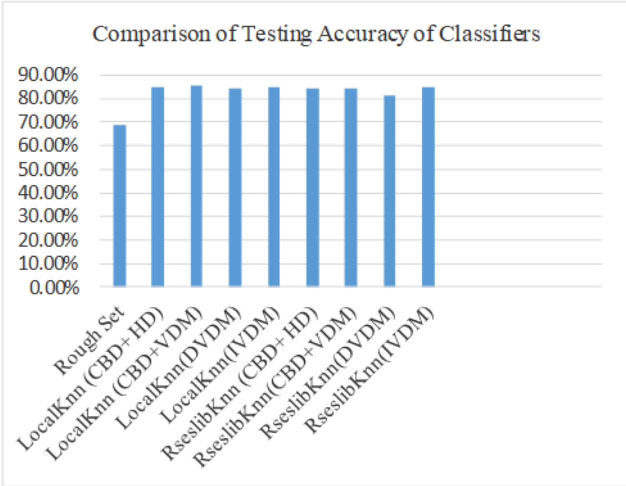

Fig.3. Comparison of testing accuracies of classifiers

V. DISCUSSION AND CONCLUSION

In this study, rough set based classifiers are applied in bearing vibration signature analysis and fault diagnosis. Out of the 3 rough set based classifiers used, one is a rule based classifier and the other two are KNN based classifiers. It is observed that rule based rough set classifier does not perform well as compared to KNN based classifiers with respect to all metrics.

LocalKnn with City block and simple value difference distance metric and an optimal value of K=13 gives best test accuracy of 85.5217 %, Kappa statistics of 0.806, Mean Absolute Error of 0.0724 and Root mean square error of 0.2691. The only problem with this classifier is its high Training Time and Classification Time of 258.61sec and 251.92 sec respectively. RseslibKnn classifier with City block and simple value difference distance metric and with an optimal value of K=15 gives test accuracy of 84.1442 %, Kappa statistics of 0.7878, Mean Absolute Error of 0.0793 and Root mean square error of 0.2816.

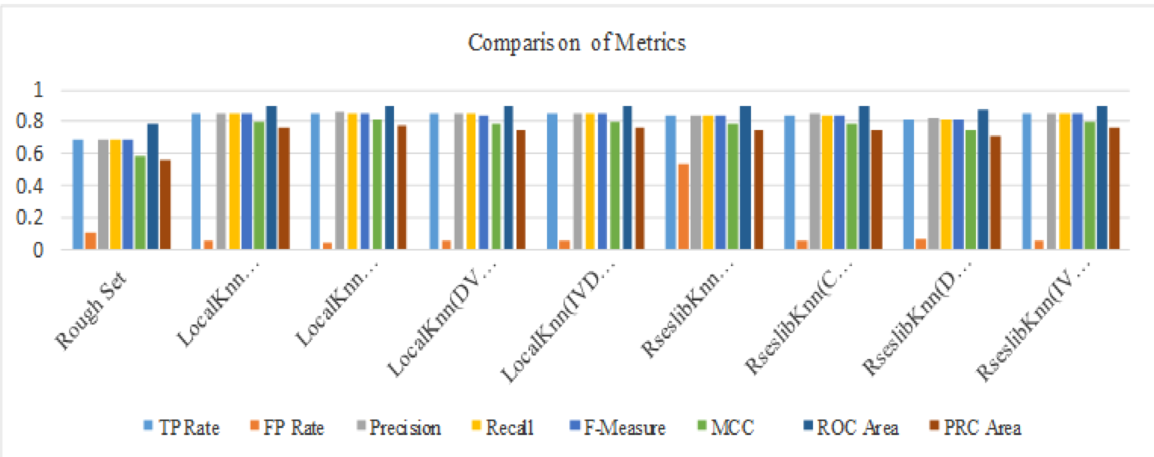

Fig.5. Comparison of various metrics for classifiers

Retrieval Number: F8610038620/2020©BEIESP
DOI:10.35940/ijrte.F8610.038620
Journal Website: www.ijrte.org

Published By:
Blue Eyes Intelligence Engineering
& Sciences Publication

Moreover, in comparison to the three classifiers used, this classifier takes considerably less time for training (9.09 sec) and classification (0.86 sec). As a result, this classifier can be very useful for training on large datasets and obtaining quick classification results.

This study proves that rough set based classifiers can be effectively utilized for bearing vibration signature analysis. For future work, the classification accuracy can be further enhanced by exploring and adding better fault descriptive features in the feature set. While adding more features in the input feature vector, it has to be taken care that the classification model does not overfit the dataset.

REFERENCES

1. Q. Wang, Y. B. Liu, X. He, S. Y. Liu, and J. H. Liu, "Fault diagnosis of bearing based on KPCA and KNN method," *Adv. Mater. Res.*, vol. 986–987, pp. 1491–1496, 2014.
2. A. Moosavian, H. Ahmadi, A. Tabatabaeefar, and M. Khazaee, "Comparison of two classifiers; K-nearest neighbor and artificial neural network, for fault diagnosis on a main engine journal-bearing," *Shock Vib.*, vol. 20, no. 2, pp. 263–272, 2013.
3. R. S. Gunerkar, A. K. Jalan, and S. U. Belgamwar, "Fault diagnosis of rolling element bearing based on artificial neural network," *J. Mech. Sci. Technol.*, vol. 33, no. 2, pp. 505–511, 2019.
4. S. Mehta, X. Shen, J. Gou, and D. Niu, "A new nearest centroid neighbor classifier based on k local means using harmonic mean distance," *Inf.*, vol. 9, no. 9, 2018.
5. A. Sharma, R. Jigyasu, L. Mathew, and S. Chatterji, "Bearing Fault Diagnosis Using Weighted K-Nearest Neighbor," *Proc. 2nd Int. Conf. Trends Electron. Informatics, ICOEI 2018*, no. March, pp. 1132–1137, 2018.
6. J. G. Bazan, H. S. Nguyen, S. H. Nguyen, and P. Synak, "Chapter 2 Rough Set Algorithms in Classification," *Rough Set Methods Appl.*, pp. 49–88, 2000.
7. A. Wojna, "Analogy-Based Reasoning in Classifier Construction," *Lect. Notes Comput. Sci.*, no. January 2005, pp. 277–374, 2005.
8. C. Xin, Y. Chen, G. Wang, and H. Dong, "Bearing fault diagnosis based on rough set," *ICSPS 2010 - Proc. 2010 2nd Int. Conf. Signal Process. Syst.*, vol. 3, no. 1, pp. 706–709, 2010.
9. X. Zhu, Y. Zhang, and Y. Zhu, "Intelligent fault diagnosis of rolling bearing based on kernel neighborhood rough sets and statistical features," *J. Mech. Sci. Technol.*, vol. 26, no. 9, pp. 2649–2657, 2012.
10. J. R. Yan, Y. Min, X. Cui, and Y. Huang, "Fault diagnosis of rolling bearing based on rough set and neural network," *Appl. Mech. Mater.*, vol. 58–60, pp. 974–977, 2011.
11. V. Muralidharan and V. Sugumaran, "Rough set based rule learning and fuzzy classification of wavelet features for fault diagnosis of monoblock centrifugal pump," *Meas. J. Int. Meas. Confed.*, vol. 46, no. 9, pp. 3057–3063, 2013.
12. W. Li, W. Pan, and S. Zhang, "Fault diagnosis using rough sets and BP networks," *2010 Int. Conf. Mech. Autom. Control Eng. MACE2010*, no. 50605021, pp. 585–588, 2010.
13. N. E. Huang *et al.*, "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis," *Proc. R. Soc.*, vol. 454, no. 1971, pp. 903–995, Mar. 1998.
14. A. Wojna and R. Latkowski, "Rseslib 3: Library of rough set and machine learning methods with extensible architecture," *Lect. Notes Comput. Sci. Springer, Berlin, Heidelb.*, vol. 10810 LNCS, pp. 301–323, 2019.
15. A. Wojna, "Rseslib User Guide," 2019.
16. "Case Western Reserve University Bearing Data Center Website." [Online]. Available: https://csegroups.case.edu/bearingdatacenter/pages/welcome-case-western-reserve-university-bearing-data-center-website. [Accessed: 15-Jan-2019].
17. D. R. Wilson and T. R. Martinez, "Improved heterogeneous distance functions," *J. Artif. Intell. Res.*, vol. 6, no. June 2000, pp. 1–34, 1997.

AUTHORS PROFILE

Chhaya Grover, is a Ph.D. research scholar in Department of Electronics Engineering in J. C. Bose University of Science and Technology, Faridabad, Haryana, India. She holds a Bachelor of Technology degree in Electronics and Communication from Institute of Engineering and Technology, Lucknow, India and Master of Technology degree in Electronics and Communication from National Institute of Technology, Kurukshetra, India. She has more than twenty years of teaching experience and currently working in the Department of Electronics Engineering in JSS Academy of Technical Education, Noida, India. Her research area is vibration signature analysis using advance signal processing for condition monitoring and fault diagnosis**.**

Dr. Neelam Turk, received B.E degree from North Maharashtra University Jalgoan, India, M.Tech. in Electronics and Communication Engineering from National Institute of Technology, Kurukshetra, India and Ph.D. degree in Electrical Engineering from National Institute of Technology, Kurukshetra, India. Dr. Neelam Turk has authored and co-authored multiple peer-reviewed scientific papers and presented her work at many national and International conferences. She has more than 20 years of teaching experience. Currently she is Chairperson & Associate Professor in the Department of Electronics Engineering in J. C. Bose University of Science and Technology, Faridabad, Haryana, India. Dr. Neelam Turk's research interests include Signal Processing, Speech processing, Wireless Communication and Communication Systems.