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Intelligent System Design for Early Diagnosis of Faults in Machine Bearings

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Abstract: Rotatory machines play crucial role in industrial sector due to their high reliability and dynamic performance. Usually, bearings are unable to sustain heavy loads due to which they deteriorate and eventually result in machine malfunctioning. Bearing fault detection at early sage can help overcome the hindrance that can be caused in production process. This research presents a novel system for the diagnosis of bearing faults at initial step. Data is gathered from food sorting machine from KIMS Hattar, Pakistan, this data is then segmented, and high frequency components are filtered using interval dependent denoising technique and Savitzky-Golay filter. Non-Linear Dynamic System features are extracted from filtered data and then dominant features are selected using Minimum Redundancy Maximum Relevance algorithm. Lyapunov Exponent and Shannon Entropy are giving highest correlation with the classes. Different classifiers are analyzed and maximum accuracy of 96.6% is obtained from ensemble subspace k nearest neighbor.

Keywords: Embedded System, Fault Detection, Machine Learning, Savitzky-Golay filter, Signal Processing.

I. INTRODUCTION

Many rotatory machines such as gearbox, wind turbine, cranes and compressors, etc. have a wide range of industrial applications. Due to excellent performance and high reliability these rotatory machines play a very crucial role in the industrial sector. Despite their outstanding reliability, they are prone to failures but using accurate predictive diagnostic techniques, these faults can be detected at an early stage [1] . A bearing fault is one of the major reasons for machine failure. In most of the machines, bearings are strained by heavy loads due to which they deteriorate and eventually result in machines malfunctioning. So, to avoid any hindrance in the production process there must be a method to diagnosis these faults at the initial stage to halt production failures. The dynamic nature of bearings subjects them to challenge when it comes to their fault detection. The main purpose of this study is to design an Intelligent System Design for Early Machine Bearing Fault Diagnosis. The major paramountcy of this system is to increase performance in terms of reliability, accuracy, low cost, low complexity, and detection of fault at an early stage to prevent production losses.

Rolling element of a machine bearings consist of several clearly mentioned components: inner race, balls or rollers, cage and outer race as shown in Fig. 1.

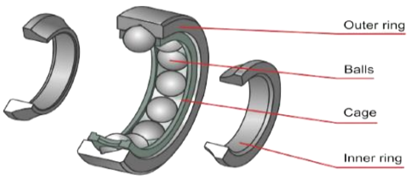

Fig. 1 Rolling element of a machine bearing.

II. LITERATURE REVIEW

A variety of techniques and methods have been used across the globe for the detection of faults due to bearings at an early stage that plays a vital role in the production process. In [1] Spectra Quest's Machinery Fault Simulator through accelerometer is used for data acquisition. Then power spectral density analysis method is used for the diagnosis of faults in bearings which include ball fault, inner race, fault outer race. In [2] multi-scale entropy and Sample entropy methods analyze the failure of an outer, inner ring of the bearing, gear wear, misalignment of bearing. These multi-scale entropies produced more effective results. In [3] DNN, SVM, backpropagation neural network, and empirical mode decomposition techniques were used for the diagnosis of faults that include eccentric gear faults and tooth crack. Comparing with other classifiers DNN gave maximum accuracy of 96.33%. In [4] deep recurrent neural network method based on deep learning along with SoftMax classifier is analyzed for the identification of faults in bearings and an accuracy of 95.27% is obtained. Data augmentation method, sample segmentation, and scaled conjugate gradient algorithm are experimented [5]. The accuracy obtained in this research is 99.6%. In [6] misalignment and unbalanced faults are diagnosed using a conditioned-based maintenance algorithm. Classification with k-nearest neighbors (KNN) gave an accuracy of 96%. In [7] accuracy of 99.87% is obtained on a dataset provided by Case Western Reserve University. Adaptive weighted multi-scale convolutional neural network technique is used for the diagnosis of bearing fault in rotatory machines. To check the authenticity of results obtained from the proposed

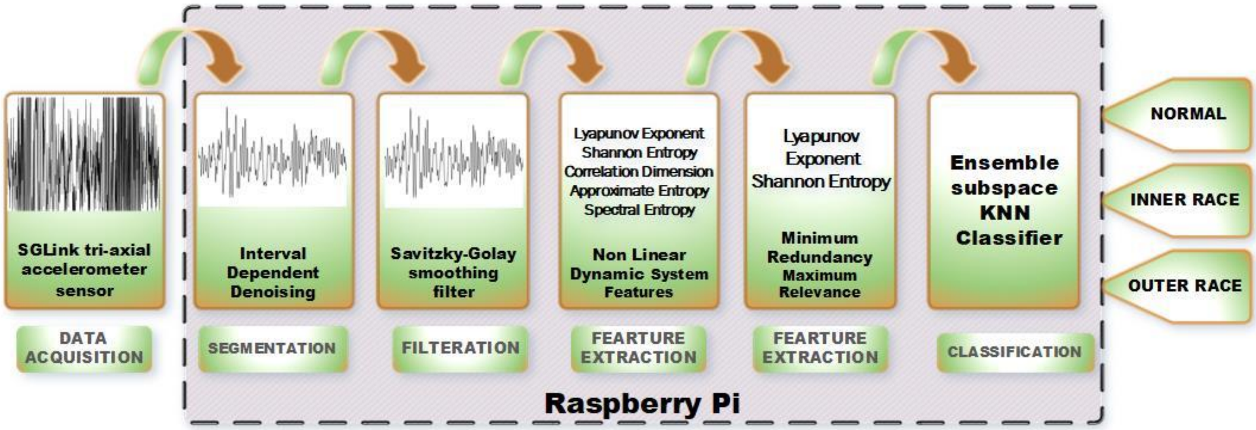

Fig 2. Block diagram of Proposed methodology

technique convolutional neural network (CNN) and other multiscale CNN, Fast Fourier transform (FFT), and inverse fast Fourier transform-based vibrational techniques are used to diagnose faults in rotatory machine bearings [8]. In [9] for feature extraction, the local temporal self-similarity technique is applied then the bag-of-words scheme is applied for classification purposes. The codebook size K is higher than the identification rate in both K-NNC and SVM. In [10] least squares support vector, integral Extension load means decomposition, and Multiscale Entropy techniques are analyzed, resulting in a maximum accuracy of 99.2%. In [11] SVM and incremental support vector machine for both Inner race (IR) and outer race (OR) faults are observed. Effective results were produced by ISVM that is 94.49% for IR and 98.73 for OR. The maximum accuracy of 95.20% is obtained by applying two novel algorithms which are extreme learning machine and wavelet auto-encoder [12]. In [13] DNN, adaptive batch normalization, and stacked autoencoders are implemented for fault detection and the accuracy obtained in this research is 96.33%.

III. PROPOSED METHODOLOGY

The block diagram of the proposed intelligent system for the early fault diagnosis in machine bearing is shown in Fig. 1. In the first step, vibrational data is acquired using the SGLink tri-axial accelerometer sensor and then passed into Raspberry Pi embedded system for further processing. The data acquired in the axial, vertical, and horizontal direction is then pre-processed using the Interval Dependent Denoising (ID) technique. After preprocessing five Non-Linear Dynamic System (NLDS) features are extracted. Before classification Minimum Redundancy Maximum Reliance algorithm (MDMR) is applied to selected features so that we can get those features that carry the maximum ability for accurate classification. In the last step machine learning-based classifier, classified the data into three classes of machine bearing faults, namely: Normal, Inner race, Outer race faults.

A. Data Acquisition

SGLink tri-axial accelerometer sensor developed by MICROSTRAIN Corporation shown in Fig. 3 is used to acquire vibrational data. Vibration data is gathered from a food processing and sorting machine (FPSM) installed at Hattar branch of KIMS, Pakistan. Raw vibrational signals of all three classes are shown in Fig. 4.

Fig. 3 Tri-axial Accelerometer Sensor.

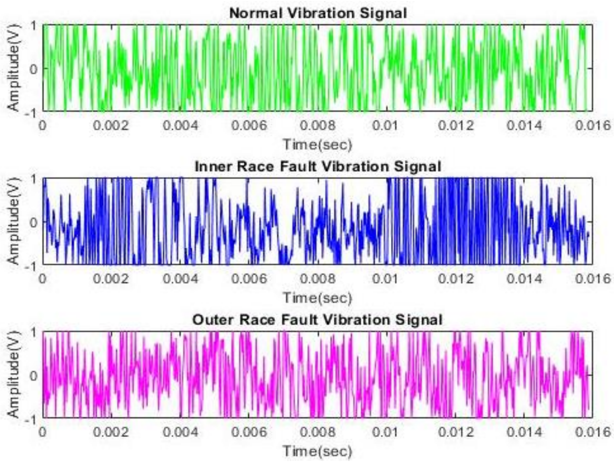

Fig. 4 Raw Vibrational signal.

Bearing failing frequencies of FPSM machine are:

- Ball Pass Frequency Outer (BFO) is 81.12 Hz.
- Ball Pass Frequency Inner (BPFI) is 118.87 Hz.
- Ball Spin Frequency (BSP) is 63.9 Hz.
- Fundamental Train Frequency (FTF) is 14.83 Hz.

BFO is also known as outer race failing frequency. It represents the number of balls or rollers that spin every time the shaft turns. BFI can also be called inner race failing frequency, physically means the number of balls or rollers going through a certain inner section of the direction any time the shaft turns full. Rolling element failing frequency is also known as BSP. This mechanically represents the sum of turns each time a bearing ball or roller turns the shaft. FTT also represents age failing frequency. It correlates to the number of revolutions which each shaft turns in its bearing cage.

B. Segmentation and Filtration

Signal deterioration due to noise is a recurring problem in almost all fields of signal processing. As a result, in practical applications, it is necessary to de-noise the received signal before further analyzing it. Thus, we applied Interval dependent denoising technique to segment out the high-frequency components of the signal from the low-frequency component. The high-frequency component obtained is then further analyzed through Savitzky-Golay filter (SGF). SGF smooths out the noise from the segmented high-frequency components of the normal and faulty vibrational signals. Its main purpose is to increase precision and accuracy without distorting the shape of the signal. As shown in Figs. 5~6 all three: normal, inner race fault, outer race fault vibrational signals are presented in time domain after applying above discussed filtering and denoising techniques.

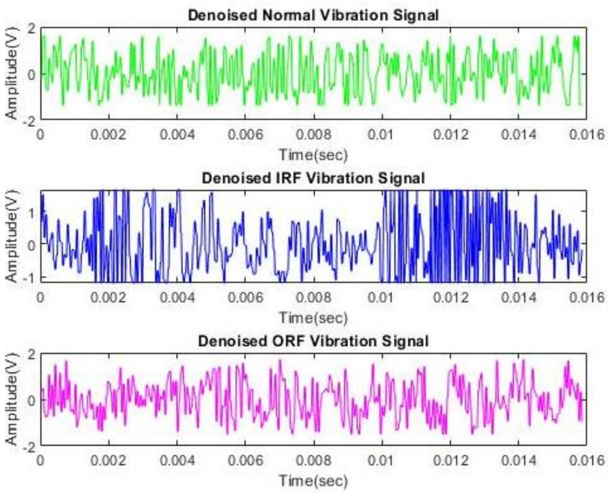

Fig. 5 Denoised Vibrational signal.

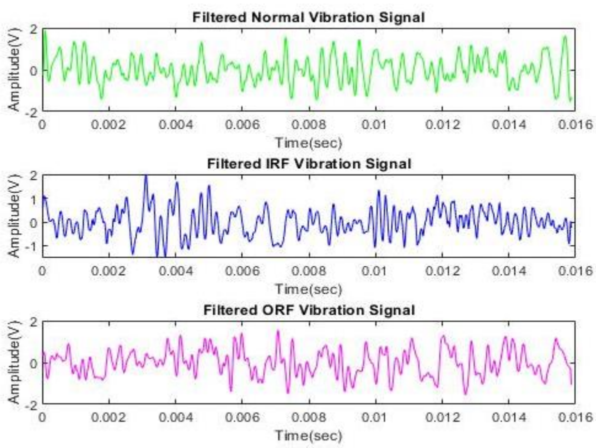

Fig. 6 Filtered Vibrational signal.

C. Feature Extraction

Feature extraction is the most crucial step in signal processing. The main aim of this stage is to figure out those discriminative attributes which can clearly diagnose the bearing fault. Bearings are one of the key causes of revolving machinery non-linearity that greatly influence the system's behavior. Nonlinearity is mostly caused by radial inner lift, uneven power, dragging preload, rigidity, ductility, number of rolling components, and so on. That’s why we needed such features which can emphasize these non-linear behaviors instead of repressing or eliminating them. Non-Linear Dynamic System (NLDS) features are extracted from the segmented and filtered vibration signal. The NLDS features that we used for classification are as follows,

- Lyapunov Exponent.
- Shannon Entropy.
- Correlation Dimension.
- Approximate Entropy.
- Spectral Entropy.

D. Feature Selection

To further select those features which are giving maximum discriminative accuracy we applied the Minimum Redundancy Maximum Relevance algorithm (MRMR). It selects those features that have a maximum correlation with the predictor and the least correlation among themselves. Lyapunov Exponent and Shannon Entropy are giving the highest correlation with the predictors as shown in Fig. 7.

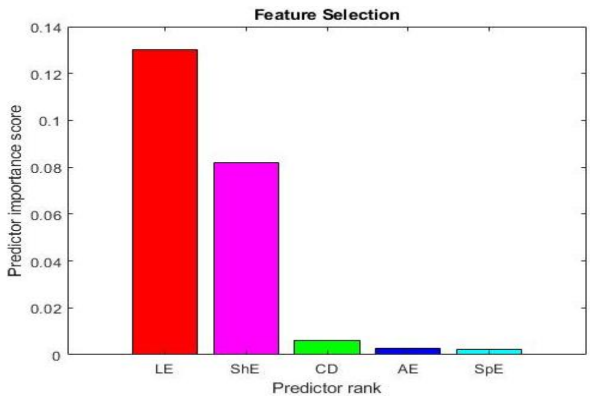

Fig. 7 Weights of NLDS features by MRMR algorithm.

E. Classification

Various classifiers were trained using these two features which include Naïve Bayes, Support Vector Machines, Logistic Regression, K-nearest neighbors, decision tree and ensemble. Ensemble subspace k-Nearest Neighbor classifier achieved the highest accuracy of 96.6% among all classifiers. Confusion matrix of ensemble subspace k-Nearest Neighbor (ES-KNN) model is shown in Fig 9.

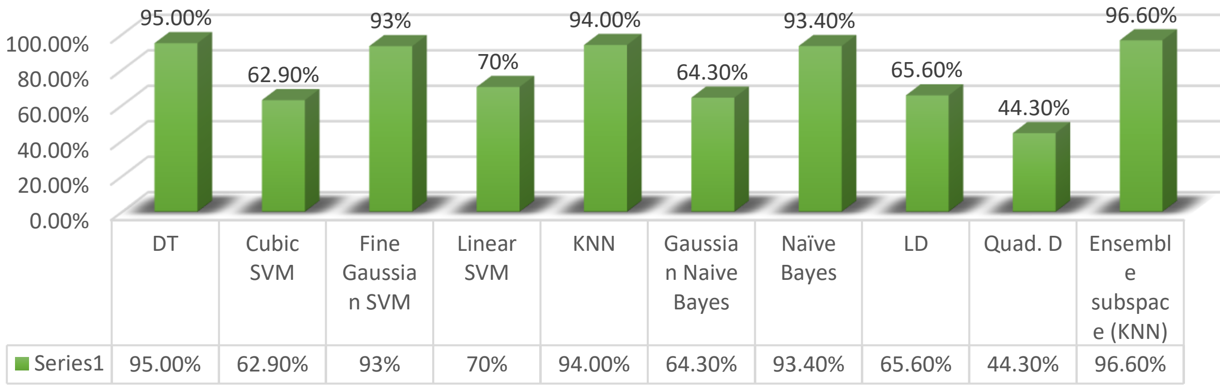

Fig. 8 Performance comparison with different classifiers.

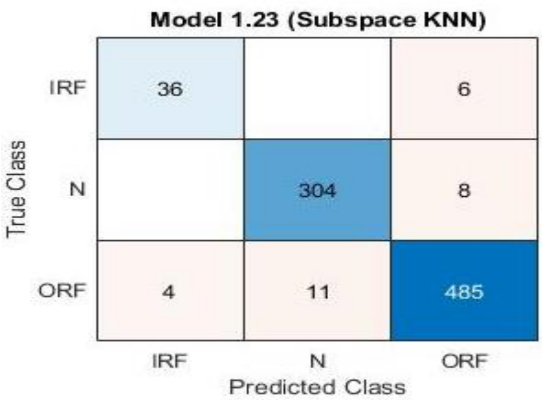

Fig. 9 Confusion Matrix ES-KNN classifier.

IV. RESULTS AND DISCUSSION

We implemented Interval dependent denoising, Savitzky-Golay filter and Ensemble-subspace KNN (ES-KNN) for the fault diagnosis and classification of

Fig. 9 Performance comparison with different classifiers. Vibrational dataset obtained using SGLink tri-axial accelerometer sensor. ES-KNN has subpace dimension of 3, and total miss-classification cost is 29.

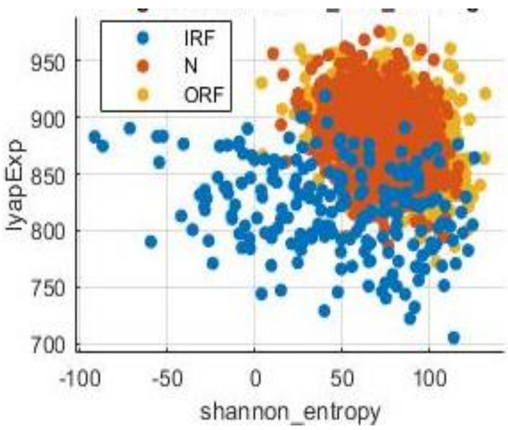

Fig. 10 Scatter plot of LE vs SE.

Classification results are analyzed in the form of comparison graph as shown in Fig 8.

Figs. 10~11 shows the scatter plot of lyapunov exponent (LE) and shannon entropy (SE), correlation dimension (CD). and approximate entropy (AE).

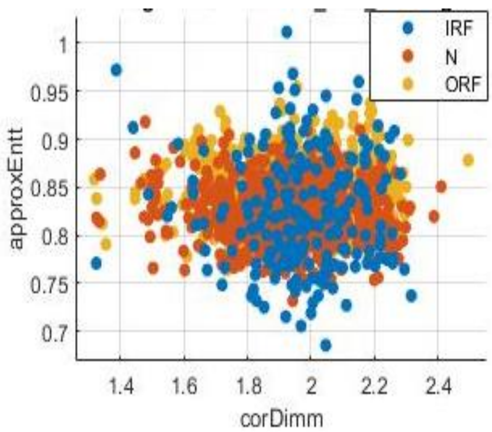

Fig. 11 Scatter plot of AE vs CD.

V. CONCLUSION

In this research we designed an embedded system for the diagnosis of faults in machine bearings. We collected dataset from food processing and sorting machine installed at Hattar branch of KIMS, Pakistan using tri-axial accelerometer sensor. The acquired vibrational data is segmented and preprocessed using Interval dependent based denoising and Savitzky-Golay filter respectively. Non-Linear Dynamic System features are extracted from vibrational data. Features having highest weights among all are selected using Minimum Redundancy Maximum Relevance algorithm. Results were scrutinized using various classifiers and Ensemble-subspace KNN model achieved maximum accuracy of 96.6%. This intelligent system deployed on raspberry pi is very efficient in terms of computational complexity. For future, our objective is to upgrade this system with more classes of faults.

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