

Fault Monitoring System for the Multistage Gear Box Based on MSTFT and GFLA Algorithm

Rohit Ghulanavar, Kiran Kumar Dama



Abstract: Gearbox functions as a significant transmission module in the mechanical devices in spite of its failure prone nature and hence there exists a need for the diagnosing the gearbox faults with an optimized solution and new methods should be engaged for improving the effectiveness, accuracy, reliability and few other such parameters. These attempts could meet the growing requirements for the condition monitoring in the detection of gear faults. The feature selection process is a notable process in the machine learning to achieve good performance in the diagnostic process. This framework builds up an innovative structure for fault diagnosis in the gearbox system. Six vibrating signals which are healthy gear signal, fault gear signal, healthy gear signal affected by noise, faulty gear signal affected by noise, distributed fault signal, and local fault signal have been generated with the prescribed dataset and the feature extraction was done by employing the Modified Short-Time Fourier Transform on the basis of Blackman window. This step was followed by selection of the features by using the combination of Genetic algorithm and Frog Leaping algorithm that is termed as GFLA. This novelty approach enhances the initialization process thereby enabling for the calculation of accurate best score calculation. The classification method is performed Support points on the basis of neural network. Finally the performance analysis with respect to the existing methodologies proved the efficiency in detecting the fault of the proposed framework.

Keywords: Gearbox fault detection, Blackman window, vibratingsignals, best score.

I. INTRODUCTION

The importance of quality control becomes more significant in the developing modern industry. The effective monitoring of product quality generally decreases the number of faults. The fault detection categorizes the abnormal and normal state of the product and it is crucial for future process and continuous working of the machines. Today various analysis for the diagnosis of the gear faults for enhancing the diagnostic process with the provision of information regarding the vibrating signals was performed with Machine learning algorithm.

The three important factors for the optimization of GFD (gear fault detection) in signal processing comprises of the feature extraction, feature selection and classification[1]. Here initialization for obtaining the best score should be considered greatly. Fault diagnosis is carried out with the help of condition parameters which are interconnected with the statistical measures from signals in time and frequency

Domains in addition to this, the parameters that are related to the time- frequency domain consist of few of the significant information on the condition of the machineries[2]. The set of condition parameters which are processed along with the diagnostic algorithms are also extended by utilizing the parameters that are related to the time-frequency domain. The above mentioned set of condition parameters are also known with the name of features in the problems present in the classification. By considering the large number of feature candidates which are available mainly for the diagnosis of fault, the feature selection issue that is occurred after the process of feature extraction is still reckoned as one of the important research topic in the case of employing the diagnosis based on the machine learning[3]. Certain condition parameters are selected due to the failure nature of the features and it is not that much simple or easier in identifying the best suitable condition parameters that are capable of granting the good diagnostic information, if any fault is occurred initially. The fault which start to exhibit few symptoms is referred to as the initial fault[4]. Few minor scratches and wear present in the face of the tooth cannot be identified sometimes in the maintenance inspections that are organized. And this is considered as one of the examples of the initial fault. This faults are closely associated to the first stage of the severe circumstances which might result in the loss of device function and then mostly these type of faults are generally occurred in the rotating machineries[5].

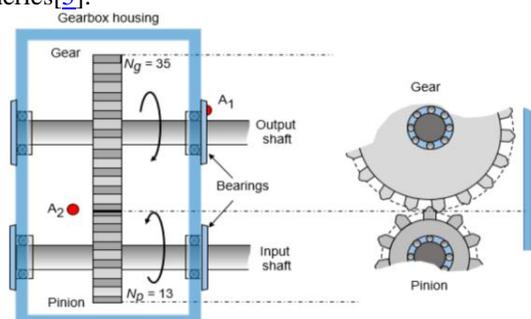


Fig 1. Gear box housing [6]

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The proper detection and diagnosis of these initial faults are still considered as one of the significant research problems which must be enhanced in the real life industrial applications.

On the contrary, the availability of huge amount of illustrations for training the classifiers is not normal or usual among the real life industrial environments. When compared to other traditional classifiers, RF-based models consist of enhanced level of performance in this case. The main contribution of the paper is to optimize the diagnosis of the fault in gearbox by improving the signal processing steps such as feature extraction by MSTFT feature selection by GFLA and Classification by SNN method.

A. Organisation of the paper

The remaining division is specified as mentioned below: Section II provides the brief explanation of the existing methods relevant to the research work is discussed in the related works. Section III deliberates the implementation process of the fault detection. Section IV illustrates the comparative investigation of projected methodology with the prevailing methods and accomplishes the research work based on our results and examination. Section V concludes this research work.

II. RELATED WORKS

This chapter deals with the literature survey for detecting the gear fault diagnosis. [7]The paper proposed a knowledge based mechanism for the establishment of fault diagnosis. It focused on the diagnosing the planetary gear packs that possess various types of faults and unequal samples present in the samples with the use of transmission error. In this technique, the best technique which comprises the significant features was chosen with the various two selection process. Many ensemble algorithms were employed for sample training methods. Here addressing of the imbalance ratio found between sample classes have been performed. The weak learners were identified directly by the genetic algorithm. At last the efficiency of the suggested system have been determined by the comparative analysis. This paper analysed the importance of inculcating the class imbalance method in the procedure thereby decreasing the misinterpretation of the normal and fault products. This pave way for producing superior quality products.[8]The work performed the feature comparison that was extracted from current signals, acoustic emission, and vibration in the time domain for the determination of 8 level pit severity in gearbox. The acoustic emission, vibration and current signals was obtained with the use of gearbox test bed[9]. It is followed by the extraction of the 20 features in time domain in each signal[10]. The corresponding features were ordered by the Chi squared and passed to the KNN classifier that allowed the performance of the accuracy of the classification and features.[11]This paper attempts to solve the issues such as the influence of Kernel function during the fault identifying ability by SVM ,and also, it focused in the difficulty in finding the predominant parameters. For the purpose a SVM on the basis of ABC algorithm have been presented. The features regarding the fault were extracted on the basis of Kernel function and EEMD. The method the Gauss Kernel SVM parameters was optimized

and the efficiency was compared with the GA, PSO and ABC algorithm. The observations depicted that the ABC algorithm proves to be better with respect to accuracy and time. The final results enhanced the gearbox fault recognition rate.[12]The research focused on the fault recognition in the spur gears by choosing the good condition parameter set on frequency and time that are extracted from the vibrating signals. The schema was done with the use of GA and a classifier on the basis of random forest in the supervised network. The values of condition parameters have been decreased around 66% concerning the original size by employing GA, however the permissible accuracy was 97%.

This method was experimented on the real vibration signals by addressing various fault classes, under various running circumstances of velocity and load. [13].The paper suggested ADSAE method for the diagnosis of gear wearing fault by comparatively original vibration data. The technique in framed on the wearing fault diagnosis by means of innovatively combining with the data augmentation and deep sparse algorithm. The observations predicted that ADSAE could greatly raise the network generalization capability and robust that possesses high precision on the basis of severity in gear wear. This research comprehensively illustrates the significant insight into gear fault on the basis of deep learning.[14]The paper employed an auto encoding learning method for machine fault diagnosis. Diagnosis of gradual faults in high-speed gear pairs using machine learning[15].

The artificial FSA was utilized for the optimization of the important parameters for adapting the signal features.FD of electrical locomotive roller bearings and gearbox. From the results it was observed that the suggested method was readily investigated for future study.[16] This paper classifies the multi faults of high speed gearbox on the basis of ML method. These kinds of faults that comprises of tooth breakage and pitting[17]. In this paper the rotational speed exceeds up to 10,000 rpm. The pinion face width and pitting have been found to be 15 mm and 1.5 mm.The suggested ML technique outperforms training and testing accuracy of 100% and 99% .The predicted method could able to furnish prior detection and finding the health of fast gearbox.[18] This paper proposed the STFT on the basis of Blackman window. This had been implemented for the reduction of the spectral leakage and the respective spectral interpolation method was applied to remove the picket fence impacts. The simulation results displays that the suggested technique could able to enhance the dynamic frequency with minimized time.

[5]This paper suggested VMD could able to choose an accurate mode number. The signals are decomposed into various VMD modes and utilized for the diagnosis of gearbox fault. The statistical structures are being extracted from the choose modes and then passed on to ELM for the classification of fault. The study offered a mean for the strategy of gearbox diagnosis.[19]The work recognized various faults at varying rotating speed with RMI and SMI was applied for the selection of sensitive gear fault significance.

The work compared the suggested with existing algorithm and proved to be better than the existing ones. elaboratelydescribed in the following Fig 2.

III. PROPOSED WORK

The proposed work of the paper have been The proposed flow depicts the overall framework of the system.

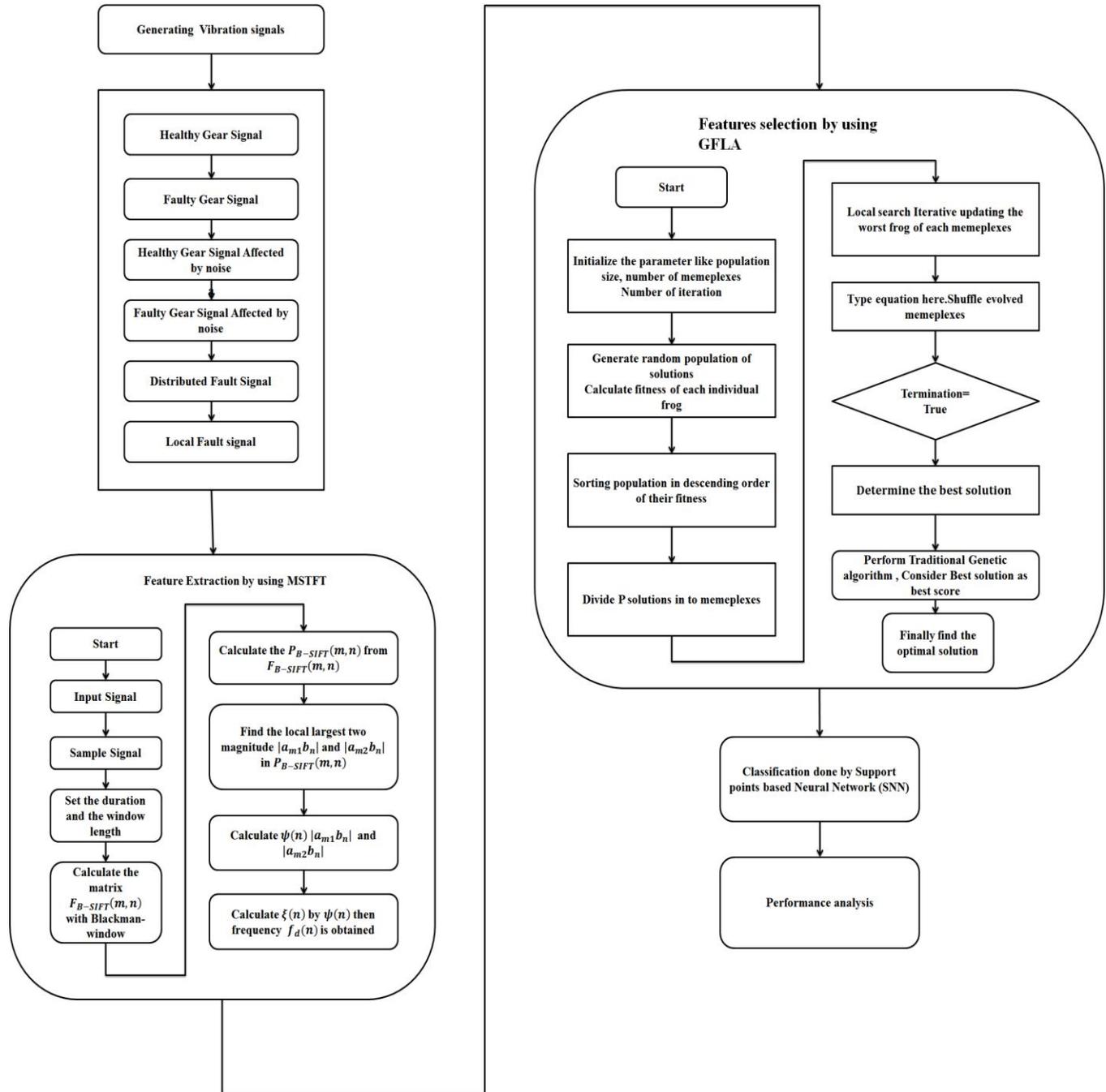


Fig 2. Overall flow of the proposed model

The vibration signals are generated with the use of time synchronous averaging and the enveloping the spectra. By employing the dataset description, the following signals are generated namely healthy gear signal, fault gear signal, healthy gear signal affected by noise, faulty gear signal affected by noise, distributed fault signal, and local fault signal. These generated signal are subjected to modified Short-Time Fourier Transform on the basis of Blackman window. This is implied to decrease the spectral leakage and the corresponding interpolation method was applied for the elimination of picket fence effects. The spectral interpolation method that was implemented on the P matrix that could enhance the frequency measurement accuracy. The extracted features are choose by means of GFLA which is the combination of Genetic algorithm and Frog Leaping algorithm and could able to resolve the issue of original power loss minimization and the maximization of voltage stability of the entire framework. This method is on the basis of observation, imitation and the designing the frog groups during location searching that possess huge food availability. The Shuffled frog leaping algorithm employs the following steps. The number of meme lexes and the number of frogs have been selected. By implying the random generation required population was generated. The frogs are arranged with respect to the fitnessvalue. Then on the basis of the modification rule, a local search have been applied in all the meme plex for improving the worst frog position. Then the framework accepts the new fitness value possessing population. Or else the acceptable frog limits was generated. The last two prescribed steps have been repeated for all the prescribed meme lexes which finish one full iteration. Now the frogs as per the previous steps have been shuffled. These algorithm have been repeated till the expected scenario have been met or the large number of iterations have been completed. In order to overcome the disadvantages of Genetic algorithm such as designation of objective function and obtaining the exact operation seems to be quietly difficult and apart from that since GA is highly expensive and time consuming, the proposed method built up an GA in combination with frog leap algorithm for proper initialization process. This accomplishes the best score finding that leads to the foundation of optimal solution. After that the classification was performed by the Support point based neural network followed by the performance analysis.

A.Feature Extraction

The feature extraction of the signals have been performed by using the Modified Shot Time Fourier Transform. The corresponding algorithm is depicted below.

Algorithm I: Feature extraction

Modified Shot Time Fourier Transform (MSTFT)

Input: $Data_{sig}, w_{window}, f_{S_{sampfreq}}, n_{fft}, H_{hop}$

Output: $S_{spec}, T_{time}, f_{freq}$

1. Determine the length of the $Data_{sig}$
 $Data_{len} = length(Data_{sig})$
2. Create window by using
 $w_{window} = create\ black\ man\ window.$
3. Determine the length of the w_{window}
 $win_{len} = length(w_{window})$
4. Compute the number of unique fft points
 $no_{uni_pt} = \frac{1 + n_{fft}}{2}$

5. Compute the number of signal frame

$$no_{sig} = \frac{Data_{len} - win_{len}}{H_{hop}}$$

6. $MSFTF_{val} \rightarrow$ Create zero matrix with size of $no_{uni_pt} \times no_{sig}$

7. For $p=0$ to $no_{sig} - 1$

Signal segment windowing with examination window

$$win_{seg} = Data_{sig}(1 + pH_{hop} : win_{len} + 1 * H_{hop})w_{window}$$

$Xdata_{fft} \rightarrow$ Perform the n_{fft} point Fast Fourier Transform for $Data_{sig}$

Update the $MSFTF_{val}$

$$MSFTF_{val}(:, 1 + p) = Xdata_{fft}(1 : no_{uni_pt})$$

End

8. Compute Time and frequency vector

$$T_{time} = \frac{win_{len} : H_{hop} : \frac{win_{len}}{2} + (no_{sig} - 1)H_{hop}}{f_{S_{sampfreq}}}$$

$$f_{freq} = (0 : no_{uni_pt} - 1) \frac{f_{S_{sampfreq}}}{n_{fft}}$$

9. Calculate the coherent amplification of the window

$$C_{co_am} = \frac{\sum_{i=1}^{win_{len}} w_{window\ i}}{win_{len}}$$

10. $S_{spec} = \frac{MSFTF_{val}}{\frac{win_{len}}{C_{co_am}}}$

11. if n_{fft} is odd

$$S_{spec}(2 : end, :) = S_{spec}(2 : end, :) * 2$$

else

$$S_{spec}(2 : end - 1, :) = S_{spec}(2 : end - 1, :) * 2$$

end

12. Finally convert into amplitude spectrogram.

B.Feature Selection

Considering the individual advantages of Genetic algorithm and Frog leaping algorithm these two have been combined for the selection of features.

Algorithm II: Feature selection

Genetic based frog leaping Algorithm (GFLA)

1. Initialize the required parameter
 $N_{pop} = X; N_{grp} = Y; I_{iter} = Z; N_{cyc} = 1; R_{radius} = R$
2. $OS_{opti} \rightarrow$ Get the optimal solution by using default SFLA algorithm
3. Compute the lower bound value
 $B_{lower} \rightarrow OS_{opti} - R_{radius}$
4. Compute the upper bound value
 $B_{upper} \rightarrow OS_{opti} + R_{radius}$
5. For $k = 2 : X$
 $OS_{opti\ k} \rightarrow$ Randomly generate the initial solution with in the interval

End

6. Calculate the fitness function for the all solution
7. Sort the value based on fitness value
8. Group the solution
9. for $I_{iter} = 1$ to Z

for $n = 1$ to N
 $OS_{opti_{n,temp}} = OS_{opti_{n,worst}} + OS_{opti_{n,best}} - OS_{opti_{n,worst}}$
 wherer $OS_{opti_{n,best}}$ is the n th group to get a new solution

$F_{fitness_{n,temp}}$
 = calculate the fitness function for $OS_{opti_{n,temp}}$

if ($invalid(OS_{opti_{n,temp}}) \& \& F_{fitness_{n,temp}} < F_{fitness_{n,worst}}$)

$OS_{opti_{n,worst}} = OS_{opti_{n,best}}$
 else

$OS_{opti_{n,best}} = OS_{opti_{n,worst}} + OS_{opti_{n,best}} - OS_{opti_{n,worst}}$

$F_{fitness_{n,temp}}$
 = calculate the fitness function for $OS_{opti_{n,temp}}$

if ($invalid(OS_{opti_{n,temp}}) \& \& F_{fitness_{n,temp}} < F_{fitness_{n,worst}}$)

$OS_{opti_{n,worst}} = OS_{opti_{n,best}}$
 else

$OS_{opti_{n,best}} =$ randomly generate the solution

While ($!invalid(OS_{opti_{n,best}})$)

$OS_{opti_{n,best}} =$ randomly generate the solution

end

$OS_{opti_{n,worst}} = OS_{opti_{n,best}}$

End if

End if

End for

Shuffle the entire frog

Sort all the value

Group all the value

End for

10. $B_{bestsolution}(N_{cyc}) =$
 get optimal solution from the cuttent cycle
11. $F_{fitness_{best}} =$
 find the fitness function for $B_{bestsolution}(N_{cyc})$
12. $OS_{opti_1} = B_{bestsolution}(N_{cyc})$
13. $N_{cyc} = N_{cyc} + 1;$
14. $R_{radius} = \lambda * R_{radius}$
15. while ($N_{cyc} < 3$ or $F_{fitness_{best}}(N_{cyc} - 1) < F_{fitness_{best}N_{cyc} - 2}$)
16. final ($B_{bestsolution}(N_{cyc} - 2)$) // compute the best score
17. $fea_{val} \rightarrow$ Run traditional genetic algorithm use final as fitness function.
18. $feature_{selected} \rightarrow S_{spec} > fea_{val}$ select the feature from S_{spec} greater then fea_{val}

C. Classification

The classification method is based on the Support Vector Machine and Probabilistic Neural Network.

Algorithm III: Classification

Support points based Neural Network (SNN)

1. $Prior_{svm} \rightarrow$ Perform Multi class Support Vector Machine , compute Prior probabilities for each class
2. Compute Gaussian kernel of each known input vector using
3. $Y_{i,j} =$

$$\exp\left(-\frac{feature_{selected} - feature_{selected_{i,j}})^T \cdot (feature_{selected_{new}} - feature_{selected_{i,j}})}{2\gamma^2}\right)$$
4. Compute class conditional probability of each class using classmate kernels
 $\{Y_{1,1}, Y_{1,2}, Y_{1,3}, \dots, Y_{1,|S_1|}\} \rightarrow P_1 = \frac{1}{|C_1|} \sum_{j=1}^{|C_1|} Y_{1,j}$
 $\{Y_{2,1}, Y_{2,2}, Y_{2,3}, \dots, Y_{2,|S_2|}\} \rightarrow P_2 = \frac{1}{|C_2|} \sum_{j=1}^{|C_2|} Y_{2,j}$
 \dots
 $\{Y_{NS,1}, Y_{NS,2}, Y_{NS,3}, \dots, Y_{NS,|S_{NS}|}\} \rightarrow P_{NS} = \frac{1}{|S_{NS}|} \sum_{j=1}^{|S_{NS}|} Y_{NS,j}$
5. Chose the class with higher class conditional probability assigns the selected class as the class of the new input data $feature_{selected}$
 $Argmax\{P_i\} \quad 1 \leq i \leq NS$

IV. DATASET DESCRIPTION

The dataset for the proposed work is as follows.

Number of teeth on pinion $Pinion_{no} = 13$

Number of teeth on Gear $Gear_{no} = 35$

Input Pinion shaft frequency $freq_{ip} = 22.5$

Compute Gear shaft frequency

$$freq_{op} = \frac{freq_{ip} \cdot Pinion_{no}}{Gear_{no}}$$

Compute Gear Mesh frequency (Hz)

$$Freq_{mesh} = freq_{ip} * Pinion_{no}$$

Create pinion waveform $pinion_{waveform}$, Gear waveform $Gear_{waveform}$ and gear mesh wave from $Gear_{mesh_{waveform}}$

1. Healthy Signal

$$Healthy_{signal} = pinion_{waveform} + Gear_{waveform} + Gear_{mesh_{waveform}}$$

The generated healthy signal has been depicted in this figure 3(a)

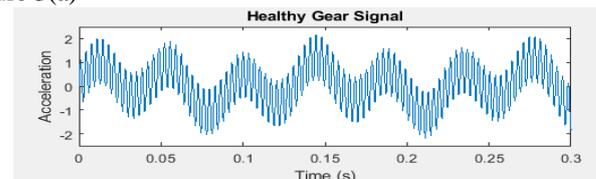


Fig 3(a) Healthy Gear Signal

2. Healthy Noise Signal

$$Healthy_noise_signal = Healthy_signal + randomnoise$$

The generated healthy noise gear signal have been depicted in this figure 3(b)

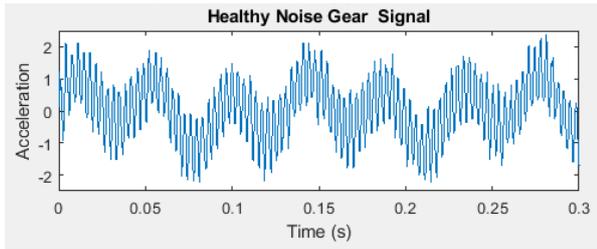


Fig 3(b) Healthy Noise Gear Signal

3. Faulty Signal

$$Faulty_signal = Healthy_signal + X_{per}$$

4. Faulty Noise Signal

$$Faulty_noise_signal = Faulty_signal + randomnoise$$

To compute a distributed fault, introduce three sideband $Side_{band}$ components of decreasing amplitude on either side of the gear-mesh frequency.

5. Distributed Fault Signal

$$Distributed_signal = Faulty_noise_signal + Side_{band}$$

The generated distributed fault signal have been depicted in this figure 3(c)

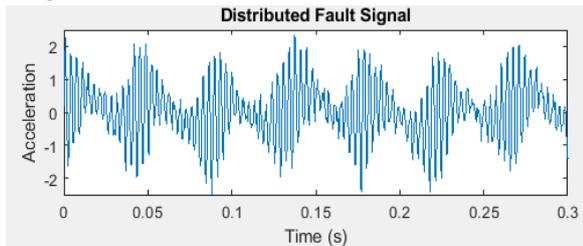


Fig 3(c) Distributed fault Signal

6. Local Fault signal

The generated Local fault Signal have been depicted in this figure3(d)

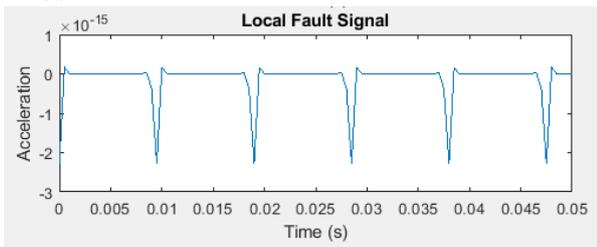


Fig 3(d) Local fault Signal

$$num_{roll.ele} = 8$$

$$diameter_{roll.ele} = 0.02$$

$$pitch_{roll.ele} = 0.12$$

$$\theta = 15$$

$$freq_{bpfi} = \frac{num_{roll.ele} * freq_{ip}}{2} \left(1 + \frac{diameter_{roll.ele}}{pitch_{roll.ele}} + \cos \theta \right)$$

Model each impact as a 3 kHz sinusoid windowed by a Kaiser window

$$f_{impact} = 3000$$

Compute time wave form t_{impact}

$$x_{impact} = \sin(2\pi f_{impact} t_{impact}) * Kaiser\ window$$

$$Local\ faulty = 0.33 * Conv(x_{comp}, x_{impact})$$

V.PERFORMANCE ANALYSIS

The following explains the performance analysis of the proposed system.

A.Overall performance measures

The performance measures like sensitivity, accuracy, specificity, Recall, precision, Jaccard coefficient, F score and missed classification have been analyzed for the proposed and existing models. The results of the proposed methodology outperforms with respect to the efficiency and effectiveness when compared with the existing models. These illustrations are shown in Fig 4 and 4(a). Least missed classification and maximum value of F- Score and Jaccard coefficient of the proposed system proved the idea used in this fault detection framework.

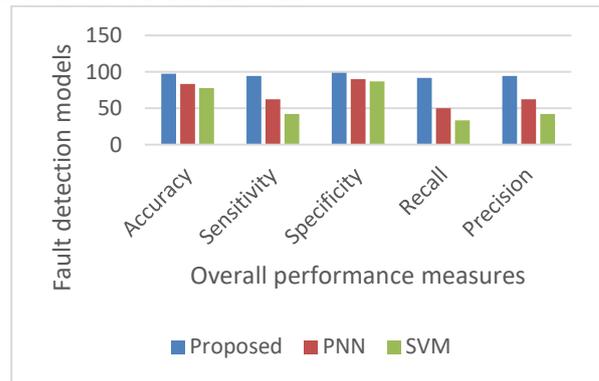


Fig 4.Efficiency of the performance measures of proposed and existing.

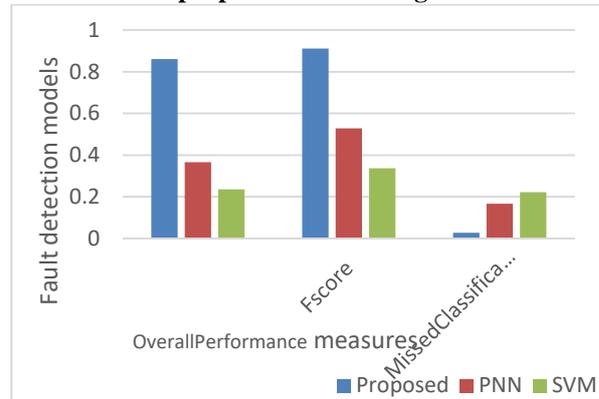


Fig 4(a). Efficiency of the performance measures of proposed and existing.

B.During 20 iterations

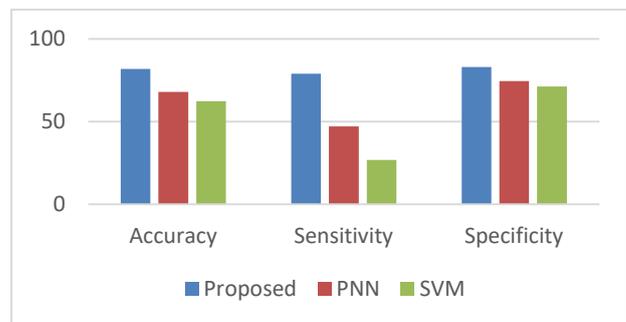


Fig 5. Performance measures of proposed and existing during 20 iterations.

The figure 5 shows accuracy, sensitivity and specificity analysis of the proposed and existing approaches during 20 iterations. The accuracy of the proposed system during 20 iterations is found to be 81.72%, the sensitivity being 78.94 and the specificity is found to be 82.98. These values outperforms the existing PNN and SVM models.

C. During 40 iterations

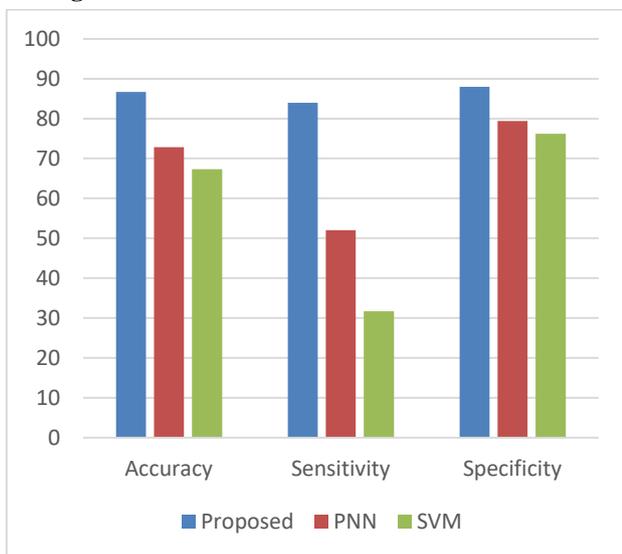


Fig 6. Performance measures of proposed and existing during 40 iterations.

The figure 6 shows accuracy, sensitivity and specificity analysis of the proposed and existing approaches during 40 iterations. The accuracy of the proposed system during 40 iterations is found to be 86.72%, the sensitivity being 83.94 and the specificity is found to be 87.98. These values are proved the proposed method outperforms compared than existing PNN and SVM models.

D. During 60 iterations

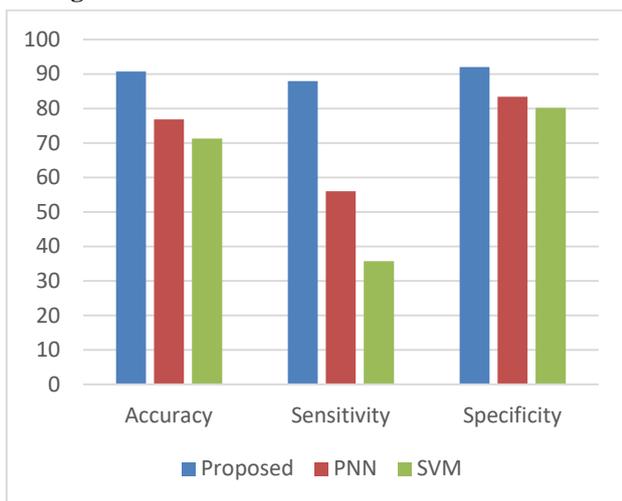


Fig 7. Performance measures of proposed and existing during 60 iterations.

The figure 7 shows accuracy, sensitivity and specificity analysis of the proposed and existing approaches during 60 iterations. The accuracy of the proposed system during 60 iterations is found to be 90.72%, the sensitivity being 87.94 and the specificity is found to be 91.98. These values outperforms the existing PNN and SVM models.

During 80 iterations

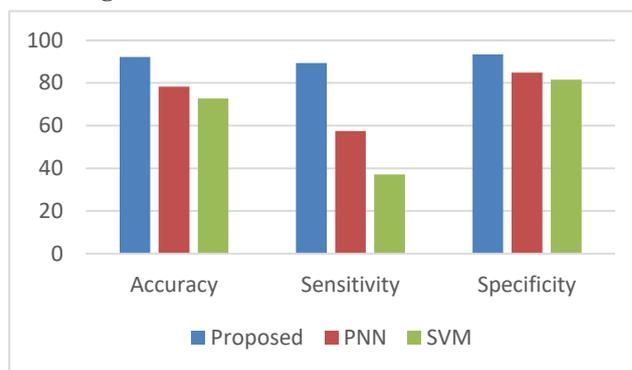


Fig 8. Performance measures of proposed and existing during 80 iterations.

The figure 8 shows accuracy, sensitivity and specificity analysis of the proposed and existing approaches during 80 iterations. The accuracy of the proposed system during 80 iterations is found to be 92.12%, the sensitivity being 89.34 and the specificity is found to be 93.38. These values outperforms the existing PNN and SVM models.

E. During 100 iterations

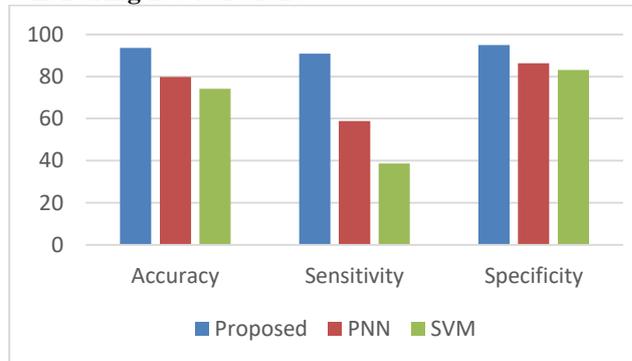


Fig 9. Performance measures of proposed and existing during 100 iterations.

The figure 9 shows accuracy, sensitivity and specificity analysis of the proposed and existing approaches during 100 iterations. The accuracy of the proposed system during 100 iterations is found to be 93.62%, the sensitivity being 90.84 and the specificity is found to be 94.88. These values outperforms the existing PNN and SVM models.

VI. CONCLUSION

In spite of its nature of failure prone, the gearbox possess the very significant function of the module that is responsible for the transmission of mechanical devices. Therefore, a necessity of diagnosing the faults occurring in the gearbox is raised. With the aid of the various new approaches and optimized solutions the effectiveness, accuracy, reliability and various other parameters are enhanced. The growing requirements for the detection of faults in the gear are satisfied. For achieving an enhanced performance in the diagnostic process, a framework that deals with the innovative layout for the diagnosis of fault in the gearbox is developed. Six vibrating signals that are healthy gear signal, fault gear signal, healthy gear signal affected by noise, faulty gear signal affected by noise,

distributed fault signal, and local fault signal are generated with the prescribed dataset. The process of feature extraction is performed by employing the Modified Short-Time Fourier Transform on the basis of Blackman window. This step is followed by the selection of the features by using the combination of Genetic algorithm and Frog Leaping algorithm that is termed as GFLA. The initialization process is enhanced by this novel technique and helps in estimating the accurate best score. Classification is carried out by the Support Points based on the Neural Network. Then in the last the performance analysis is carried out with respect to the existing methodologies and this proves that the efficiency of detecting the fault is improved in the proposed methodology when comparing it with the existing ones.

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