GEARBOX FAULT MONITORING SYSTEM FOR FOUR WHEELER ENGINE USING CNN

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Abstract - *In order to totally inspect the health conditions of the gearbox or any rotating machinery, condition monitoring systems are accustomed acquire real-time data from. The source and thus huge amount of data is acquired after very long time of collection. We use different quite applied science techniques for monitoring machinery health conditions, like artificial neural networks (ANNs), support vector machine (SVM), fuzzy inference, etc. There are various methods in use for the fault diagnosis of gearboxes, intelligent fault diagnosis methods are widely used can tackle complicated mechanical diagnosis problems effectively because of its constructive learning mechanism, fault tolerant methods and high non-linear regression ability. The three main methods of fault diagnosis are:*

(1) Signal acquisition, (2) feature extraction, and (3) fault classification.

Deep learning, also called deep neural networks (DNN) a ''deep'' layer structure which allows to under the representations of complicated data with multiple levels of abstraction. Starting with the raw input, DNN automatically find complicated and complex structure in large data-set and learn important features layer by layer. It's obvious that the advantage of the feature brain of DNN just meet the necessities of an adaptive feature extraction method for mechanical fault diagnosis. There lies a decent potential and a critical must utilize DNN and its feature brain for fault diagnosis of mechanical systems.

Key Words: MATLAB, data-set, Classification, Feature extraction, Signal processing. Training data, testing data.

1. INTRODUCTION

As the necessary components of most mechanical equipments , gears are the most widely used in the system of car engine system. Due to the complex structure and penurious condition of the transmission system, gears can be easily deface, which causes in increased failure probability. Therefore it is the stipulation for effective gear-box fault detection methods that can successfully detect and identify the fault feature information of gears.

In the past decade, vibration signal analysis method has become one in every of the foremost effectively used mechanisms to diagnose the faults within the gearbox. Liu et al. [1] proposed a feature extraction and kit fault diagnosis method supported vibrational mode decomposition, singular value decomposition, and convolutional neural network (CNN).Kuai et al. [2] used the tactic of permutation entropy of Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) Adaptive Neuro-fuzzy Inference System (ANFIS) to form gear fault diagnosis during a planetary gearbox. Moreover, vibration signals don't seem to be easy to be measured in hot temperature, high humidity, high corrosion, and toxic and harmful environments, that the vibration signal analysis method for gear fault diagnosis is proscribed by its requirement of contacted measuring. Considering that, it's in urgent have to develop acoustic-based diagnosis (ABD) methods to beat this disadvantage via non-contact measurements.

There is an urgent need for diagnosis methods which will effectively analyze massive data and automatically provide accurate diagnosis results. This sort of methods is named intelligent fault diagnosis methods, during which AI techniques, like artificial neural networks (ANNs), support vector machine (SVM), fuzzy inference, etc., are used for distinguishing machinery health conditions [3–5]. Supported the results produced by the various intelligent diagnosis methods, it's possible to require appropriate maintenance actions and ensure healthy operation of the machines [6]. Correspondingly, intelligent fault diagnosis methods are widely investigated and applied within the field of fault diagnosis of rotating machinery [7]. Samanta [8] extracted time-domain features and employed three optimized neural networks to detect pump faults. Additionally, Samanta et al. [9] for representing the health conditions of induction motor then decision tree and adaptive neuro-fuzzy inference system (ANFIS) were utilized for distinguishing the faults. Moreover, Tran et al Widodo et al. [10] calculated statistical features from the measured signals and administrated RVM and SVM to diagnose the bearing faults. Lai et al. introduced cumulants as input features and used radial basis function network because the fault classifier. a way was presented by Bin et al.

1.1 LITERATURE REVIEW

During the past many years, the majority the researchers used DNN solely as a classifier or a feature choice technique for mechanical fault identification within the similar thanks to ancient intelligent strategies. Options square measure extracted by numerous signal analysis strategies initially. Then these extracted options square measure accustomed train and check the DNN models. Li et al. [1] applied a deep belief networks (DBN) to diagnose gearboxes and bearings with data point options in time, frequency and time-frequency domains. [2]Chen et al. Extracted many time and frequency options and used a convolutional neural network (CNN) to classify totally different health conditions of a casing. [3]Verma et al. developed a thin auto-encoder (SAE) and extracted time, frequency and riffle domain options because the model input to observe air compressors. [3]Shao et al. Composed AN optimized DBN to boost eighteen time-domain options and diagnose faults of bearings. During this stage, though DNN models square measure applied in mechanical fault identification. [5]0. Janssens et al. explored CNN to diagnose bearing housings with raw frequency information. The vibration information of the bearing housings is preprocessed through quick Fourier transformation (FFT) and inputted into CNN to find faults.[6]. Zhao et al. designed a convolutional long remembering networks (C-LSTM), during which a CNN is employed to extract native options from raw sensory information, and a LSTM is provided to predict tool wear. Sun et al. incontestable a SAE to extract options and monitor the health conditions of an induction motor. Kuai et al. used the tactic of permutation entropy of Complete Ensemble Empirical Mode Decomposition with reconciling Noise (CEEMDAN) reconciling Neuro-fuzzy illation System (ANFIS) to form gear fault identification during a planetary casing. AIDA et al. Compared the benefits and downsides of non-contact, air-coupled unbearable sensors and speak to electricity unbearable sensors in health observation of rotating machinery. [7]Scanlon et al. used non-contact mike sensors to amass acoustic signals of rotating machinery for predicting residual life. Hecke et al. Designed a brand-new acoustic emission sensing element technique to find the fault mode of the bearing. With the event of array measure technology, some researchers additionally applied this technology in acoustic-based identification. W.B. Lu et al. projected a casing fault identification technique that's supported the abstraction distribution options of a sound field.[8] Rong-Hua Hu et al. projected a rolling bearing fault identification technique, that is predicated on NAH and a grey-level gradient co-occurrence matrix (GLGCM).utilized for identifying the faults[8].Samantha extracted time-domain options and used 3 optimized neural networks to find pump faults. Additionally,[9] Samantha et al. utilized time-domain options to characterize the bearing health conditions and used ANNs and SVM to diagnose faults of bearings. applied mathematics options were extracted by Tran et al Moreover, [10]Tran et al. calculated options from thermal imaging supported bi-dimensional empirical mode decomposition, then input chosen options into connection vector machine (RVM) for fault classification.

2. METHODOLOGY

The whole concept of Gearbox fault monitoring system has its inception in realizing the unexpected failures of the gearbox without any warning leading to avoidable downtime and a catastrophic loss of human lives. Wondering if these losses can be minimized without cumbersome human mechanical interference by warning the driver about the gearbox conditions periodically. With the completion of our topic's literature review, the physical hardware sensors and other necessary equipments needed were carefully analysed and also evaluation of every problem faced by the preliminary version of our work has been meticulously done to ensure quality and efficiency

Software Requirement: Windows 10 or Linux Operating system and we carried out our entire project on MATLAB R2018a platform and tool boxes/API used were Signal Processing, Audio Processing and Machine learning.

Hardware Requirement: We have used i3 processor, 4 GB Ram and a 32GB Hard Disk.

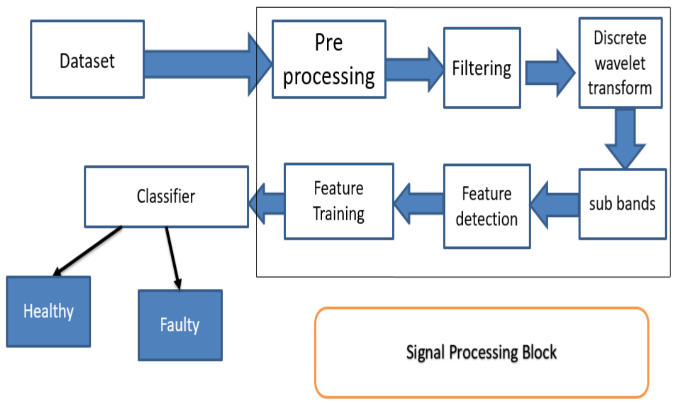

Fig-1: Methodology.

The Methodology can be divided into:

1. Data Collection
2. Data Preprocessing
3. Feature Extraction using Discrete Wavelet Transform and training
4. Fault Classification

Data Collection and Data Preprocessing: Data is obtained from the online sources, particularly from UCI repository and 2009 PHM gearbox fault data is employed to analyze the proposed method. The data collected is the representative of general, non-specific industrial gearbox data, which has 3 shafts, 4 gears and 6 bearings .The data-set consists of 3 channels 2 channels of accelerometer signals and 1 channel of tachometer signal acquired by corresponding sensors. The data-set contains 6 different health conditions of the gearbox under low load and 30Hz,40,Hz,50Hz speed .Signals were obtained for each health condition with frequency of 66.67 KHz and acquisition time of 4 seconds

1. Data Pre-processing: These signals acquired are divided into data segments first as shown in above figure, 6144 sampling points are selected as a segment .For 3 operating speeds there will be 130 rounds, thus for six conditions in total there will be 780 data segments, Now these segments will be processed by different methods to compare the feature learning performance .For the raw Time domain data, the data segments will be inputted directly into intelligent models, frequency data will be processed by FFT. The learning from the vibration data along with 8 time domain features, 32 frequency domain features and 5 wavelet domain features are employed .RMS ,kurtosis, crest factor, skewness, mean , min, max and variance are selected as time domain features and RMS of each bands as the frequency domain features

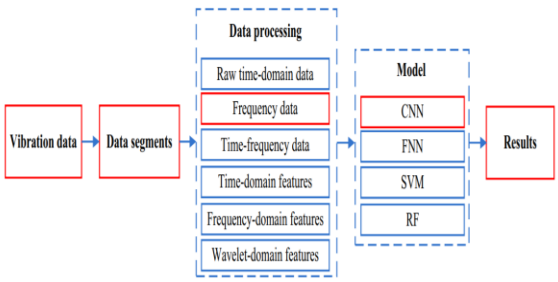

Fig-2: Flow chart of the proposed method and its comparative methods (marked in red is our proposed method).

2. Feature Extraction using discrete Wavelet Transform and feature Training: Wavelet transform decomposes the given input signal into wavelets of different scales with variable window size and disclosing the local structure in frequency domain.it is capable of providing both time and frequency domain information simultaneously has been used in nonstationary vibration signal processing and fault diagnosis. The frequency bandwidth of vibration data should be wide in order to cover higher harmonics of meshing frequency and high frequency resolution. The wavelet ⍰(t) is the square integrable function and can be described in a equation as :

$$C_{\psi} = \int_{R} \frac{|\Psi(\omega)|^2}{|\omega|} d\omega < \infty,$$

Where Ψ(⍰) is the Fourier transform of ⍰(t) a member of function can be derived from (t), equation can be written as :

$$\psi_{a,b}(t) = |a|^{-1/2} \psi\left(\frac{t-b}{a}\right),$$

Where ⍰,a ,b(t) is the member of wavelet mother function and a and b are scale and translation parameter

Some wavelet filters are used for decomposition and reconstruction, it is shown as

$$A_0[x(t)] = x(t),$$

$$A_j[x(t)] = \sum_k H(2t-k) A_{j-1}[x(t)],$$

$$D_j[x(t)] = \sum_k G(2t-k) A_{j-1}[x(t)],$$

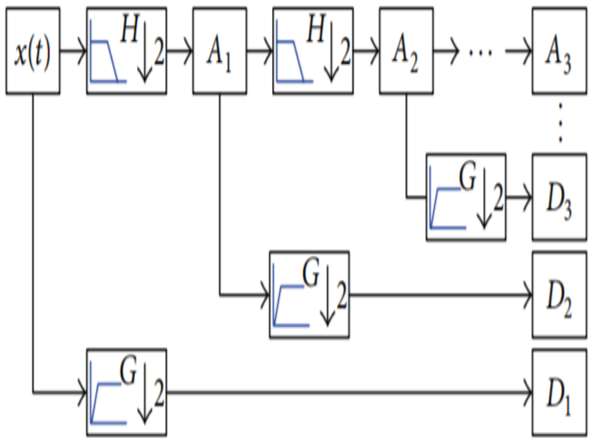

Fig-3: Decomposition procedure of J -level DWT

Where (t) is original signal, J Is decomposition level. H is wavelet decomposition filter for high pass and G is wavelet decomposition filter for low pass filtering, Aj and Dj are the low frequency wavelet co-efficient

3. Classification: Health conditions are diagnosed using intelligent deep learning classification techniques such as convolution neural network, SVM,

shallow artificial neural network is used, and this presents a new idea that utilizes DNN for both fault characteristic mining and intelligent diagnosis. The proposed method is compared with neural network based methods using the data-set, a neural network is a computational model based on the neuron cell structure of the biological nervous system. With a training set of data, the neural network can learn the data by using learning algorithm; here, the most common algorithm, back-propagation, is used. Through back-propagation, the neural network forms a mapping between inputs and desired outputs from the training set by altering weighted connections within the network.

3. IMPLEMENTATION

Deep learning is an artificial function which is to learn from data-set. CNN a class of deep learning extract the features from the data-set. In our project we are using MATLAB R2018a on Windows 10 that provides matrix manipulations, plotting of data and implementation of data. MATLAB provides the flexibility of high level language and certain development tools required for numeric data.

MATLAB analyses the data by extracting the segments of data and finds co-relation. In addition, to that it carries out the Fourier analysis and filtering to remove the data. In this project two types of filtering is used namely (1) Notch filter (2) Band pass filter. The input of data segment is checked for the noise and unwanted frequencies. Then, the Fast Fourier Transform (FFT) algorithm is used to compute discrete Fourier transform for the given data. Further, for more accuracy Discrete Wavelet Transform(DWT) which provides information about the range of frequencies present in the data and also provides the location of particular range of frequency.Frequency bandwidth of the vibration spectrum for gearbox fault diagnosis needs to be wide in order to cover higher harmonics of fundamental meshing frequency and also needs to have high frequency resolution in order to extract information around fundamental meshing frequency and its harmonics. The raw data is saved in the database. The raw data is pre-processed to classifier for finding the features. And then passed to classifier. The complete data-set is split into training and testing samples based on training .The training data is read to train the network. The trained data classifies the tweet.

The opening user interface has four options-(a) Data processing Features (b) Classification (c) Feature extract (d) Computed results.

Fig-4: User interface

By selecting option (a) the (I) UI pops. We choose the number of channels to take the single data-set from database. Then choose the data-set from the data-frame and plot in frequency domain and then extract the features from the single data-set and plot the frequency domain view, time domain decomposition, power spectrum of original signal(unfiltered),spectrum of band-pass filtered signal(0.200,60000)Hz ,the original time series, the band-pass filtered time series in(0.200,60000)Hz. The below figure shows the features extracted for single data-set from data-frame.

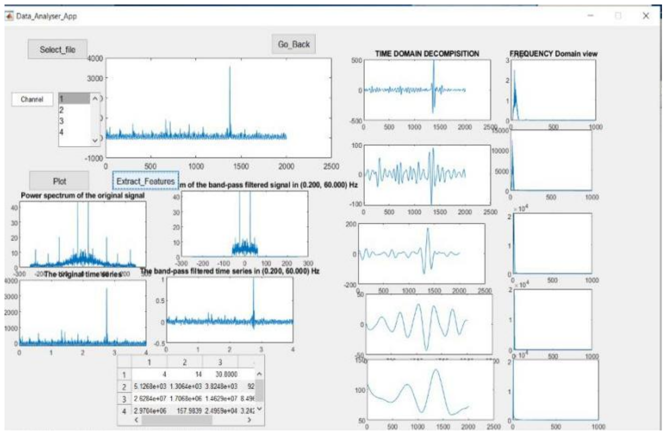

Fig-5: Feature of single data-set.

In (b) the data signal is segmented into parts (alpha, beta, gamma, theta, and delta).The data segments are used to calculate power, standard deviation, and variance, mean squared error, root mean square, values. These values are used for classification.

Classification are for three situations-(1) Healthy (2) Faulty type 1 (3) Faulty type 2.

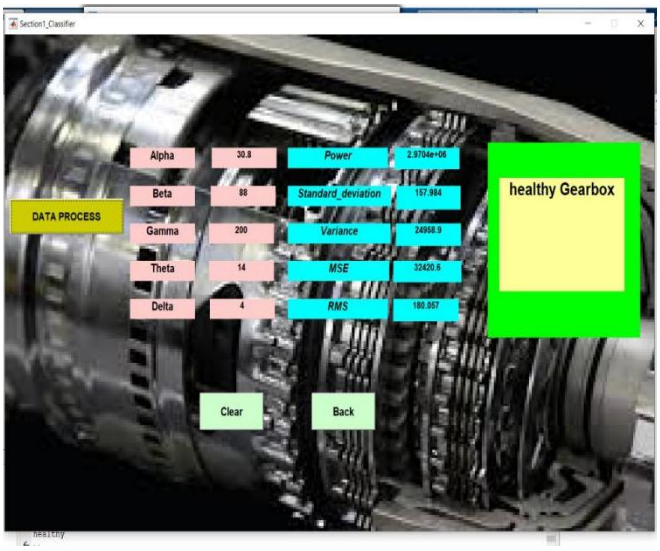

Fig- 6 : Classification

In (c) the user interface pops with Extract Features option, you choose option Extract Features, it extracts the features of data-set. The training is complete.

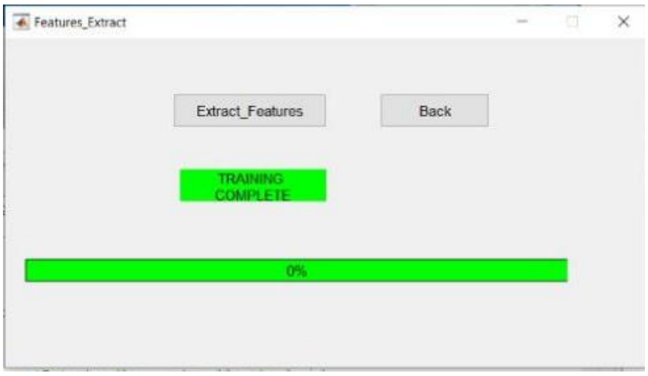

Fig-7: Feature extraction.

In (d) confusion matrix is a table used to describe the performance of classification model on test data for which true values are known.The accuracy obtained was around 100% under various conditions since the data-set is lab generated. Confusion matrix identifies the errors in the classifiers and shows the comparison between the predicted values and expected values.

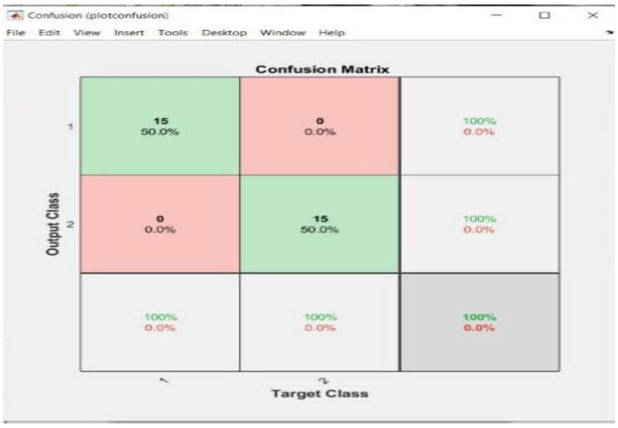

Fig-8: Confusion matrix.

Below figure shows the CNN configuration for number of layers and neurons.

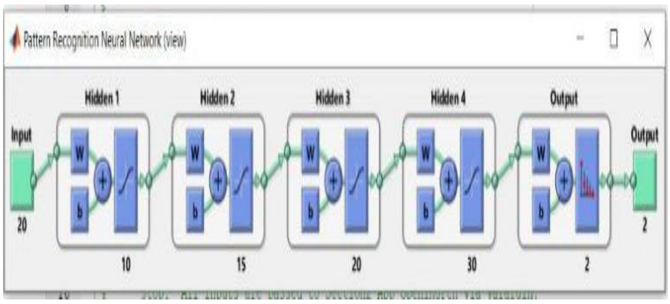

Fig-9: CNN layers.

4. CONCLUSIONS

This paper presents a CNN-based intelligent method for diagnosing the faults of substances box levers. The effectiveness of the proposed method is verified using sampled data-set obtained from gearboxes. These data-set contain massive samples involving different health conditions under various operating conditions. Through the diagnosis results of those data-set, it's shown that the proposed method is in a position to mine fault characteristics from the frequency spectra adaptively for various diagnosis issues and effectively classify the health conditions of the machinery. Since mining fault characteristics automatically, the proposed method is a smaller amount addicted to human labor or prior knowledge about signal processing techniques and diagnostic expertise than this CNN-based methods. So supported the proposed method, new applications are often achieved easily. There is also some guidance for the employment of the proposed method. First, we should always find the proper algorithms to process the info and feed it to the machine to process the info to induce the particular desired and efficient outputs. Then half coefficients of the frequency spectra should be used because the coefficients are symmetric within the spectra.

Finally, a deeper network like CNN with algorithms like online learning and with gradient descent and feed-forward network might be tried for your applications although the CNN has performed well during this paper. Within the proposed method, CNNs are trained by frequency spectra. Therefore, it only works for 4-wheeler gear box and reciprocating machinery whose measured vibration signals are periodic. It's interesting to directly train the CNNs using raw signals within the time domain so on apply them to other machines.

While the manual selection of exact parameters to choose and train the model accordingly for deep learning methods is quiet cumbersome and it takes a lot of trial and error methods to decide for the hyper-parameter tuning and is time consuming. Thus is it more meaning full to investigate more efficient methods on deep learning mean while simply we assembled the frequency domain time data to make it processed by CNN.

REFERENCES

[1] C. Li et al., Gearbox fault diagnosis based on deep random forest fusion of acoustic and vibratory signals, Mech. Syst. Signal Process. 76 (2016) 283–293.

[2] Z. Chen, et al., Machine fault classification using deep belief network, in: 2016 IEEE International Instrumentation and Measurement Technology Conference Proceedings, 2016, IEEE..

[3] N.K. Verma , et al., Intelligent condition based monitoring of rotating machines using sparse auto-encoders, in: 2013 IEEE Conference on Prognostics and Health Management (PHM), 2013, IEEE.

[4] H. Shao, et al., Rolling bearing fault diagnosis using an optimization deep belief network, Meas. Sci. Technol. 26(11) (2015).

[5] O. Janssens et al., Convolutional neural network based fault detection for rotating machinery, J. Sound Vibe. 377 (2016) 331–345.

[6] J. Lee, F.J. Wu, W.Y. Zhao, M. Ghaffari, L.X. Liao, D. Siegel, Prognostics and health management design for rotary machinery systems—reviews, methodology and applications, Mech. Syst. Signal Process. 42 (2014) 314–334.

[7] K. Worden, W.J. Staszewski, J.J. Hensman, Natural computing for mechanical systems research: a tutorial overview, Mech. Syst. Signal Process. 25 (2011) 4–111.

[8] B. Samanta, Artificial neural networks and genetic algorithms for gear fault detection, Mech. Syst. Signal Process. 18 (2004) 1273–1282.

[9] B. Samanta, C. Nataraj, Use of particle swarm optimization for machinery fault detection, Eng. Appl. Artif. Intell. 22 (2009) 308–316.

[10] V.T. Tran, B.-S. Yang, M.-S. Oh, A.C.C. Tan, Fault diagnosis of induction motor based on decision trees and adaptive neuro-fuzzy inference, Expert Syst. Appl. 36 (2009) 1840–1849.

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