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Technological Evolution in the Fault Diagnosis of Rotating Machinery: A Review

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Abstract:
Background*: Rotating machineries are widely used in a various type of industrial applications. For reliable working of mechanical system, fault diagnosis of rotating element is the most important and crucial task. Over the past decades, fault diagnosis of mechanical systems has progressed with the evolution of machinery in terms of complexity and scale. High scale machinery require health monitoring and fault diagnosis to guarantee their reliable performance. Research on fault diagnosis of rotary machines has grown rapidly in the recent years. Objective of this paper is to review the recent research trends in the field of rotating machinery fault diagnosis in terms of these aspects: vibration generation mechanism, fault mechanism, signal acquisition and signal processing and fault diagnostics, artificial neural network, support vector machine etc.*
Results*: With the advent in technology and complexity in operation of machinery, it is found that Artificial Neural Network, Machine Learning techniques are very effective to ensure safe operation of machinery.*
Conclusion: *With the increasing complexity of mechanical structures, it is increasingly important to monitor and diagnose the condition of rotating machinery. In many cases, the vibration signal and shaft orbit are important features that reflect the state of mechanical equipment. Therefore, an efficient feature extraction and fault diagnosis method plays a significant role in the operation management and condition monitoring of mechanical equipment.*

Key Word*:* ***Deep learning, Fault diagnosis, Intelligent diagnostics, Rotating machinery, Signal processing, Support vector machines***

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I. Introduction

Rotating machinery is one of the most important and critical components of many mechanical systems applied in modern industry, civilian and military applications such as sugar and process industry, pumps, compressors, steam turbines, wind turbines, machine tools, automobiles, industrial fan, aircraft engines, high speed train, aerospace, nuclear power plants, ship building, railways and many more. High load, high temperature, high and varying speed or inevitable fatigue are the key components for unexpected mechanical faults in the system. If the presence fault is not diagnosed at incipient stage then it may cause catastrophic failure which leads to breakdown of the system as a whole and loss of productivity. In view of this, it is very important to early diagnose the faults of the rotating machinery.

Many techniques are used for the fault diagnosis (FD) to monitor the health conditions of the rotating machinery such as the Vibration-based FD [1], Sound based FD, Torque based FD, Acoustic Emission based FD [2], Thermal analysis with infrared imaging [3], wear abrasive method and rotating encoder-based FD [4] etc. The rotating elements of any machine have unique characteristic vibration profile that is also known as a vibration signature. This vibration signature is associated with specific failure mode. Change in the vibration profile is the basis for Vibration based Condition Monitoring. The rotating elements exhibit high harmonic oscillations when on the verge of failure. These characteristics have attracted the researchers to apply Vibration based condition monitoring in the field of machinery fault diagnostics. Rotating machinery consists of shaft, bearings, gear box, propeller and other rotating machine elements and these machine elements operate at high speed and under fatigue loading. Failure of the elements leads to loss of productivity and breakdown and as such fault diagnosis of all this elements is essential. Basic research direction of rotating machinery fault diagnosis is as shown in Fig. 1.

The main objective of this paper is to review the journey in the technological advancements in the domain of fault diagnosis of rotating machinery from traditional methods to advance intelligent methods. To Start with, the vibration generation mechanism is explained for rotating components like shaft, rotor, bearings and gears with different types of faults in rotating Machinery. In the next section, sensor techniques with signal acquisition is explained to acquire signals/vibrations followed by signal processing techniques like Fourier transform and Wavelet transform. Finally, fault diagnosis with traditional methods and with advanced or intelligent methods is discussed. In the last section, conclusion based on the review is presented.

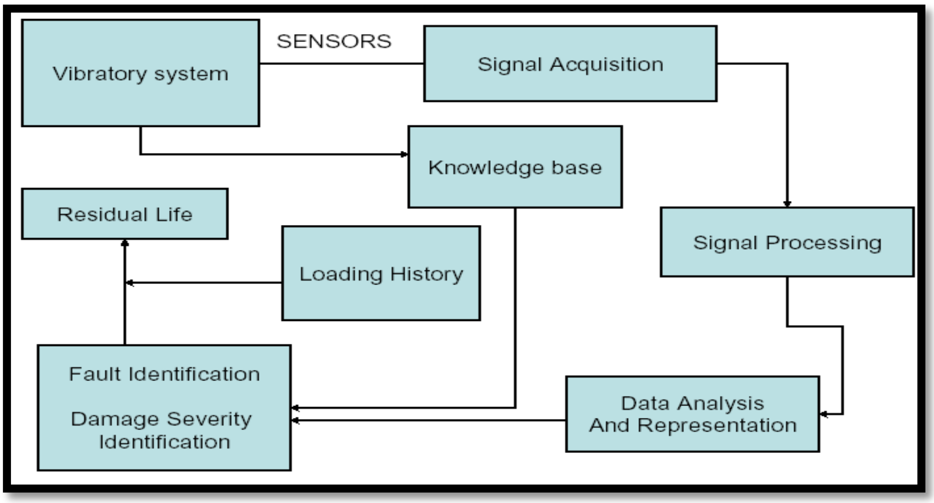

Fig. 1 Basic research direction of Rotating Machinery fault diagnosis [5]

II. Vibration Generation Mechanism in Rotating Elements

Rolling elements due to their constructional feature and other reasons act as a source of vibration. The various causes of vibration in rolling elements are: rolling surface irregularities and defects, varying compliance vibrations, shock pulses when lubrication layer is disrupted, excitation due to friction forces, rotor oscillation forces, and interaction with other components. Defects in rolling element bearings are broadly classified as distributed defects and local defects. Surface roughness, waviness, misaligned races and off-size rolling elements are the examples of distributed defects. In case of defects present on localized region, a pulse of very short duration is generated due to variation of contact stress at the defect. This gives rise to vibration. Localized defects include cracks, pits and spalls on the bearing surfaces. Defects in Rolling Element Bearings are inner case defect, outer case defect. The vibration behavior of a ball bearing having influence of localized defects on the outer race and inner race. [6-8] In the working process, the bearing may be damaged due to improper assembly, poor lubrication, water, and foreign body invasion, corrosion, overload, etc. [9].

For rotating element gears, vibration can be thought of as a ratio of the forces acting on the gear to its dynamic stiffness. The backlash, error of the gear transmission, the unbalanced inertia mass, the time varying mesh stiffness of tooth faces and the time varying support stiffness of geared system, change the ratio, i.e. Vibration which characteristics can reflect symptoms of a lot of faults or defects. The location in the spectrum of all the gear related frequencies requires the knowledge of a minimum amount of gearbox data. These data are the rotating speed of the input shaft or the output shaft and the number of teeth of the different gears. In this way there will be no doubt in the identification of the gear frequencies and their sidebands. Characteristic spectrum of a gear assembly in good condition is shown in Fig. 2. The frequencies associated directly with a gear assembly are as follows:

- Gear mesh frequency (GMF): It is characteristic of each gear assembly and appears in the frequency spectrum regardless of the condition of the gears. Its amplitude depends significantly on the load at the time of reading. It is calculated according to the following formula where; Z is the number of teeth and RPM is the rotating speed of the gear.

$$GMF = Zp \times RPMp = Zg \times RPMg \quad (1)$$

- Gear mesh frequency side bands: these are frequencies equidistant from the gear mesh frequency. These sidebands correspond to the rotating frequency of the pinion and the gear. They are very important in the diagnosis of the gear assembly, since they indicate if the gear or the pinion are in bad condition.
- Hunting tooth frequency (HTF) to calculate it the number of assembly phases (N_a) must be calculated in advance as described in the following section. Indicates the frequency with which a tooth of the gear engages with the same tooth of the pinion. In case of damage to one tooth of the gear and another of the pinion, the maximum vibration will occur when both faults come into contact. This frequency is very low so it is difficult to locate in the frequency spectrum, being detected more easily in the time waveform.

$$HTF = GMF \times \mathrm{Na}\, Zp \times Zg \quad (2)$$

- Assembly phase frequency (APF): indicates that as a result of wear, the space between teeth and the teeth profile has changed.

$$APF = GMF \times \text{Na} \tag{3}$$

- Gear natural frequencies: when some kind of gear deterioration develops the natural frequencies of the gears can be excited.
- Ghost or phantom frequencies: correspond to a relatively rare defect that shows up as a frequency typically higher than the GMF but not directly related to the geometry of the gear. It is due to manufacturing errors that are driven by vibration from the manufacturing drive train and can be typically traced to the number of teeth and speed of the cutter machine.

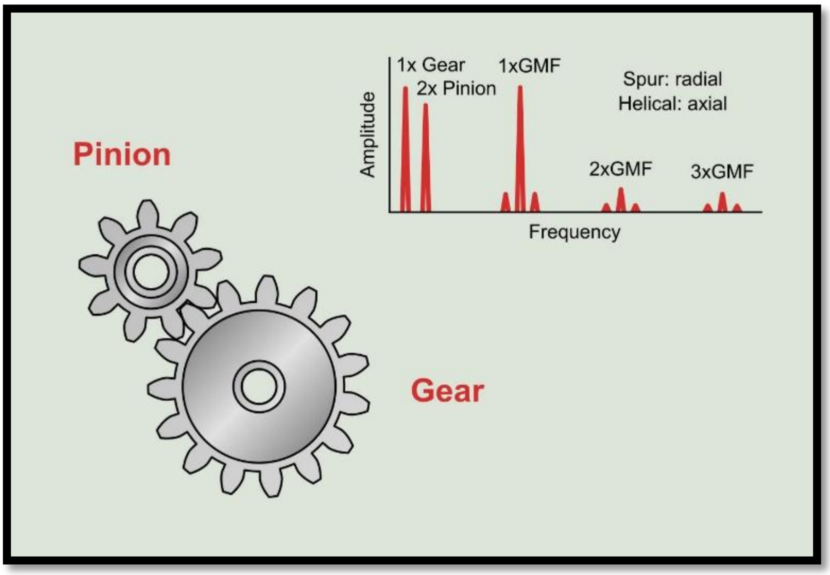

Fig. 2 Characteristic spectrum of a gear assembly in good condition

Some other causes are due to the effects of nonlinear factors such as gear machining errors, installation errors, external load changes, meshing impact and gear tooth defects. For gear tooth defects like broken tooth, cracked tooth, wear in flank surface is of three types: abrasive wear, squeezing and pitting [10], cracks in flank, root cracks, pitting and spalling of gear tooth [11]. By measuring and analyzing the machine's vibration, it is possible to determine both the nature and severity of the defect, and hence predict the machine's failure. The vibration signal of a rotating component carries the signature of the fault in the system, and early fault detection of the system is possible by analyzing the vibration signal using different signal processing techniques.

III. Feature Extraction Techniques

During vibration-based condition monitoring of rotating machinery, data is in the form of vibration signals. From the rotating components vibration signals are acquired by using data acquisition system. The sensor is used to get the input. Triaxial accelerometer is normally used to measure vibration signals from all the three direction. Accelerometer is mounted on the bearing housing. Different steps of feature extraction procedure are as shown in Fig. 3.

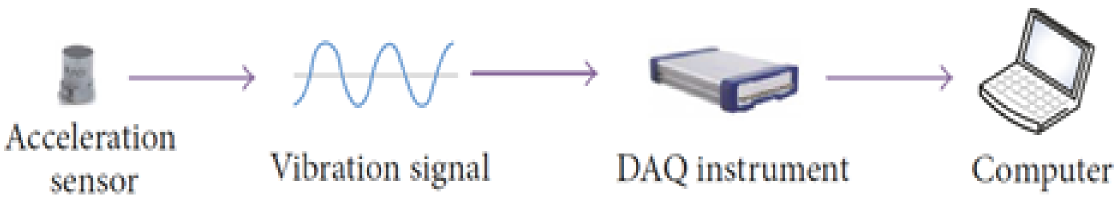

Fig. 3 Feature extraction Procedure

The purpose of feature extraction is reduction in the dimensionality of the vibration data presented for inspection without distorting the original contents of data. Different measurement techniques based on vibration and acoustics are used for detecting the defects in a rotating element. In addition to the experimental methods, the analytical methods are also used by the researchers which yield reasonably accurate results to predict the dynamic behavior of rotating elements. Apart from the experimental methods, researchers have also effectively used analytical methods to understand the vibration generation source for safe working of machines. Tandon and Choudhury [12] have developed an analytical model to predict the vibration frequencies of rolling element bearing and the amplitude of frequency components due to the presence of localized defects on different elements of a bearing. White [13] in his paper has pointed out that pulse can take into account severity, extent and age of the damage for modelling the bearing vibrations. McFadden and Smith [14] extended their earlier model to describe the vibration produced by multiple defects. The influence of multiple defects was explained by the reinforcement and cancellation of spectral lines because of differing phase angles. Su and Lin [15] extended the vibration model developed by McFadden and Smith [14] to describe the bearing vibration under diverse loading. They have reported the need of time domain analysis along with frequency domain to reliably monitor a running bearing. Patel et al. [16] have developed a dynamic model of a ball bearing in the presence of single and multiple defects on the races.

Vibration based condition monitoring methods are time- domain, frequency - domain and time-frequency analysis wavelet-based methods (Fig. 4). Frequency-domain analysis of the signal acquired from the rotating elements is the most widely used approach for health assessment. Fourier transform is a classical tool for converting data into a form that is useful for analyzing frequencies. When a defect gets struck by its mating elements, a pulse of short duration is produced and the natural frequencies of bearing elements are excited.

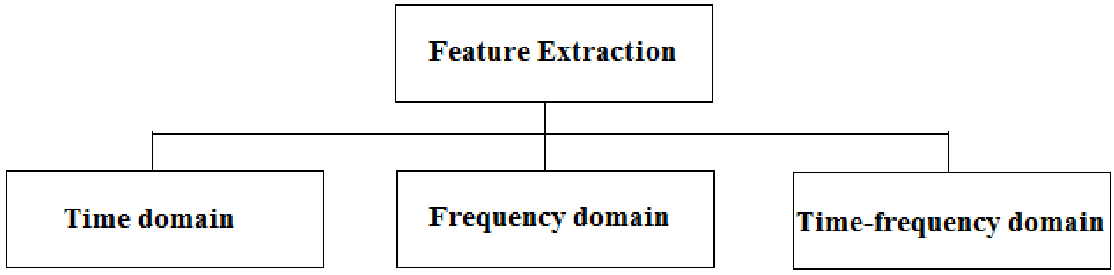

Fig. 4 Feature extraction techniques

Using expressions for characteristic defect frequency, location of a fault is detected based on peaks obtained in the spectrum. These frequencies depend on the bearing characteristics and are calculated according to the relations as shown below:
The shaft rotational frequency (f_s) which is equal to the speed of shaft is given by

$$f_s = (N/60) \quad (4)$$

The outer race defect frequency (f_{od}) is given by

$$f_{od} = \frac{z}{2}\,\frac{N}{60}\left[1 - \left(\frac{D}{d_m}\right)cos\emptyset\right] \quad (5)$$

The inner race defect frequency (f_{id}) or the ball pass frequency of the inner race is given by

$$f_{id} = \frac{z}{2}\,\frac{N}{60}\left[1 + \left(\frac{D}{d_m}\right)cos\emptyset\right] \quad (6)$$

The ball defect frequency (f_{bd}) or ball spin frequency is given by

$$f_{bd} = \frac{d_m}{D}\,\frac{N}{60}\left[1 - \left(\frac{D}{d_m}\right)^2 cos^2\emptyset\right] \quad (7)$$

Where
$\emptyset$ = contact angle
d_m = pitch diameter
z = no. of balls
N = rotational speed of shaft in rpm

These bearing characteristic frequencies are approximate as they will be affected by slipping of the elements within the bearing and spinning of the races on the shaft or in the housing.

The time-domain analysis is based on acquiring a time waveform of vibration and analysing for extracting various parameters such as root-mean-square, crest factor, skewness, cepstrum, mean, standard deviation, kurtosis etc. These parameters have been employed for the detection of faults in rotating elements. It is reported that crest factor and kurtosis are very sensitive to faults in the bearing. Frequency-domain and time-domain methods are applied independently or in conjunction to each other. The time domain parameters are defined in the following paragraph.

Root Mean Square (RMS)

The RMS value of the vibration signal can be used for primary health investigation of the machine. For a discrete vibration signal x with mean μ, RMS is given by

$$RMS = \sqrt{\left(\frac{1}{N}\sum_{1}^{N}[x-\mu]^2\right)} \qquad (8)$$

It is reported that RMS level increases with increase in fault severity level [17].

Peak Level

Peak level is an indicative of occurrences of impacts. For low-level fault, peak level is good indicator.

Crest Factor

The crest factor is a measure of spikiness of signal. It is good indicator of faults in rolling element bearings. It is the ratio of peak value to the RMS value. Crest factor above 6 indicates the faulty condition of bearing. The crest factor initially increases with the level of fault and decreases with the increase in fault severity after a particular level. The crest factor is the best candidate for robustness (consistent parameter over time) [18].

Skewness

Skewness is a measure of asymmetry around its mean. It describes asymmetry from the normal distribution in a set of statistical data. It is the third moment of the time signal, normalized with respect to the cube of standard deviation. The Skewness value can be positive or negative. Negative skew indicates that the tail on the left side of the probability density function is longer than the right side. Conversely, positive skew indicates that the tail on the right side is longer than the left side. A zero value of skew indicate that the tails on both sides of the mean balance out.

Kurtosis

Dyer and Stewart [19] proposed the use of the fourth normalized central statistical moment kurtosis for defect diagnosis of bearings. Kurtosis can be defined as the standardized fourth population moment about the mean. The amplitude distribution of a defect free bearing is generally assumed to be Gaussian. Kurtosis is a measure of the peakedness of a signal and vibration signal will contain impulsive transient events during the onset of degradation. A normal distribution has a kurtosis of 3. Kurtosis value exceeding 3 indicates degradation of a bearing. Kurtosis is given by

$$K_u = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{x-\mu}{\sigma}\right]^4 \qquad (9)$$

Cepstrum

Cepstrum is anagram of spectrum. Cepstrum is obtained by taking Fourier transform of the logarithm of the mean square density as shown in Fig. 5.

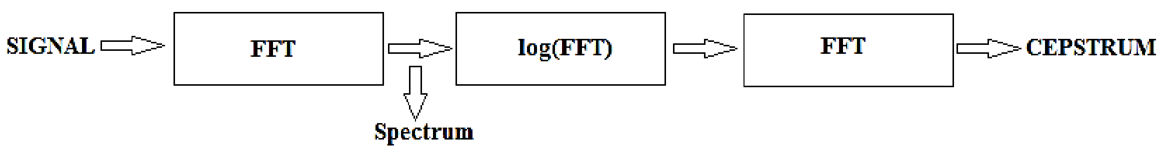

Fig. 5 Cepstrum of a signal

Cepstrum is a function of independent variable quefrency having the dimensions of time. The advantage of using cepstral analysis is that the periodic harmonics can be detected even when they are covered within a high noise level [20]. Shakya et al. [18] have investigated the influence of a defect and its severity using time domain, frequency domain and time-frequency domain parameters. The comparison among these parameters was based on the robustness, sensitivity to damage change and early detection of the faults. In some studies, it is observed that both the approaches based on frequency and time domain are used together for drawing conclusions on fault diagnosis. Frequency domain and time domain methods have some shortcomings.

Frequency domain approach is suitable for analysis of vibration signals that are produced by some periodic process. The vibration signal emitted by a rotating element can be considered as cyclo-stationary rather than periodic. Fourier transform has limited success when the signal is buried in background noise. Additionally, the measured vibration signal can also change because of fluctuating load condition.

As such the focus of the research work is on examining advanced signal processing method such as wavelet transform in the domain of rotating element fault diagnostics. In the following paragraphs, a comprehensive review is presented on the application of wavelet transform in the field of fault diagnostics in rotating machinery.

IV. Wavelet Transform for Fault Diagnosis

Many studies in the past focused on finding solutions for the shortcomings of conventional frequency and time domain techniques. As such the methods based on wavelet transform are attempted by researchers for reliable monitoring of bearings, gears, structures etc. [21-24]. Wavelet theory has emerged as a signal processing tool in many fields and has many distinct merits. It was first put forward by Morlet in 1984. Wavelets are mathematical functions that cut up data into different frequency components and each component is studied with a resolution matched to its scale by multi- resolution analysis [25]. Wavelet transform is a linear transform and uses a series of oscillating functions with different frequencies as window functions to scan and translate the signal. They are suitable for analyzing physical situations where the signal contains discontinuities and sharp spikes. The commonly used wavelet algorithms are continuous wavelet transform (CWT), discrete wavelet transform (DWT) and wavelet packet transform (WPT). Peng and Chu [26] have presented a detailed review on the application of wavelet transform in machine condition monitoring and fault diagnostics. Several main aspects were discussed such as the time-frequency analysis of signals, the fault feature extraction, the singularity detection of signals, the denoising and extraction of weak signals, the compression of vibration signals and system identification etc. Wavelets are successfully applied in machine fault diagnostics for its many distinct advantages and are suitable for the analysis of non-stationary signals and for fluctuating load conditions [21]. The ability of wavelet transform in time-frequency analysis makes wavelet suitable for the transient process analysis. When the defect on one of the elements of rolling bearing gets struck by the mating elements, the vibration signal contains jump points that are often singularity points. These singularity points such as peaks or discontinuities carry important information of the signal.

Continuous Wavelet Transform

The continuous wavelet transform is the inner product of x (t) with translate and dilate of a wavelet ψ. ψ is wavelet translated by b and dilated by a.

$$CWT\ (b,a) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t)\psi^{*}\left(\frac{t-b}{a}\right)dt \tag{10}$$

where $\psi^*(t)$ stands for the complex conjugation of ψ (t).

Above is CWT of function x € L2(R) w.r.t. wavelet ψ evaluated at translation b and dilation a. Eq. (8) indicates that the wavelet analysis is a time-frequency analysis, or a time-scaled analysis. The analysing function or windowing function ψ must satisfy certain admissibility conditions to be considered for wavelet analysis. The dilation parameter a and translation parameter b are also referred as the scaling and shifting parameters. By changing the value of dilation parameter a, the portion of the function in the vicinity of t = b can be examined in different resolutions (referred as multi-resolution analysis). By changing the value of translation parameter b, the function around the point t = b can be examined by the wavelet window piece by piece. It is possible to reconstruct the original function from its wavelet transform. The inversion formula is given by:

$$x(t) = \frac{1}{c_{\psi}} \iint w(a,b)\psi_{(a,b)}(t)\frac{dadb}{a^2} \tag{11}$$

where,

$$c_{\psi} = \int_{-\infty}^{+\infty} \frac{|\psi(\omega)|^2}{|\omega|} d\omega < \infty$$

Using above equations [27], the original signal can be reconstructed without any loss of data. Scaling parameter a is positive real and translation parameter b is positive or negative. At high frequencies, the wavelet reaches at a high time resolution but a low frequency resolution, whereas, at low frequencies, high-frequency resolution and low time resolution can be obtained. Djebala et al. [28] have proposed wavelet multiresolution analysis technique for identifying faults in rolling element bearings. Using kurtosis as evaluation metric, parameters such as the level number, the decomposition optimal vector, the sampling rate and the wavelet family were decided. For impulsive faults like rubbing, continuous wavelet transform (CWT) gives an effective method for fault analysis and detection [29]. A technique based on minimum Shannon entropy was applied by Castro et al. [30] through continuous wavelet transform for obtaining optimal shape forms of the Gabor wavelet for analysing vibrations of antifriction bearings. It is reported that wrong selection of the shape factor of Gabor function results in loss of resolution on a time-frequency basis.

Discrete Wavelet Transform

The continuous wavelet transform (CWT) is defined at all points in the plane and corresponds to a redundant (extra) representation of the information present in the function. This redundancy requires a large amount of computation time. Instead of continuously varying the parameters, the signal may be analysed with a small number of scales with varying number of translations at each scale. The discrete wavelet transform may be viewed as a "discretization" of the CWT through sampling specific wavelet coefficients. A critical sampling of the CWT given by Eq. (9) is obtained via a = 2-j and b=k2-j, where j and k are integers representing the set of discrete dilations and translations respectively. Upon this substitution, discrete wavelet transform (DWT) is obtained and is given by:

$$W(j,k) = \int_{-\infty}^{+\infty} x(t) 2^{j/2} \psi(2^{j} t - k) dt \qquad (12)$$

The term critical sampling denotes the minimum number of coefficients sampled from continuous wavelet transform to ensure that all the information present in the original function is retained by the wavelet coefficients [31]. The discrete wavelet transform computes the wavelet coefficients at discrete intervals (integer power of two) of time and scales. In discrete wavelet transform, the signal is decomposed into a tree structure of low and high pass filters. Each step transforms the low pass filter into further lower and higher frequency components as shown in Fig. 6.

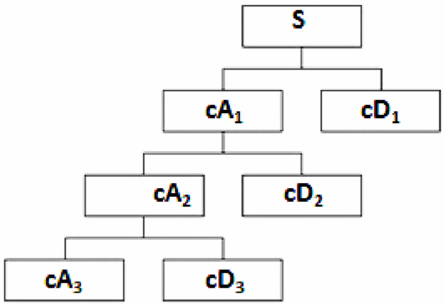

Fig. 6 DWT decomposition tree of three-level [32]

The frequency band of each filter depends on the decomposition level. The high frequency components are not analysed further. The low pass filter produces approximation coefficients and high pass filter produces detail coefficients. For example, if N_t =Total length of signal, j=DWT decomposition level, Fs=Sampling frequency, then each vector contains Nt/2j coefficients. Approximation corresponds to Frequency band [0, Fs/2j+1] while detail covers the frequency range [Fs/2j+1, Fs/2j].

At any decomposition level, the signal can be expressed as the sum of approximation and detail coefficients as follows:

$$S = A_j + \sum D_i (i \leq j) \qquad (13)$$

where A_j = Approximation coefficients at jth level

D_i = Detail coefficients

Based on discrete wavelet transform explained, Prabhakar et al. [33] analyzed vibration signals of ball bearing having single and multiple point defects on inner race, outer race and the combined faults. Using Daubechies 4 (Db4) mother wavelet, the vibration signals were decomposed up to a level of four. In order to obtain the useful information from raw data, db02 and db08 wavelets were adopted to decompose the vibration signal acquired from the bearing,

De-noising technique based on wavelet analysis was applied to decomposed the denoised signals up to 7th level by wavelet packet transform (WPT) and 128 wavelet packet node energy coefficients were obtained. [34]

Wavelet Packet Transform

The wavelet packet transform (WPT) is a generalization of the wavelet transform. There are many studies on bearing fault diagnosis using wavelet packet transform [32, 35-37]. Wavelet packet transform (WPT) decomposes not only the approximation coefficients but also the detail coefficients. In Fig. 7, an example of a wavelet packet decomposition tree to a level of three is illustrated. The sampling rate of the signal is assumed to be 24 kHz. The frequency sub-band at each node of the wavelet packet tree is shown. A split on detail coefficients leads to change in basis set and these basis sets are called wavelet packets. Wavelet packets are a collection of functions given by [35]:

$$\left\{ 2^{-j/2} W_n (2^{-j} t - k), n \in N, j, k \in Z \right\} \tag{14}$$

Above function is generated from the following sequence of functions:

$$W_{2n}(t) = \sqrt{2} \sum_i h_1 W_n (2t - l) \tag{15}$$

$$W_{2n+1}(t) = \sqrt{2} \sum_i g_1 W_n (2t - l) \tag{16}$$

where h and g are the quadrature mirror filters, $W_0(t)$ and $W_1(t)$ are the scaling function and basic wavelet respectively. The wavelet packet $\{2^{-j/2}$ Wn $(2^{-j} t - k)\}$ is a localized function of unit energy with scale 2j, translation 2jk and an oscillation parameter of n. Time scale domain signal energy show the similarity between signal and wavelet which is selected. Total energy can be obtained by:

$$E(n) = \sum_{i=1}^{n} \left| x[n] \right|^2 \tag{17}$$

where n=No. of samples of the signal

An appropriate wavelet selected as the base wavelet, must have maximum amount of energy of the wavelet coefficients. Learned and Willsky [37] have presented investigations on the feasibility of applying the wavelet packet transform for the detection and classification of transient signals buried in background noise. The method aimed at obtaining the smallest number of features for reliable classification of transient signals. Ekici et al. [38] adopted wavelet packet transform for decomposing simulated signals of transmission lines. The signals were decomposed to a level of three and the energy and entropy of wavelet coefficients were calculated for each faulty current and voltage waveform.

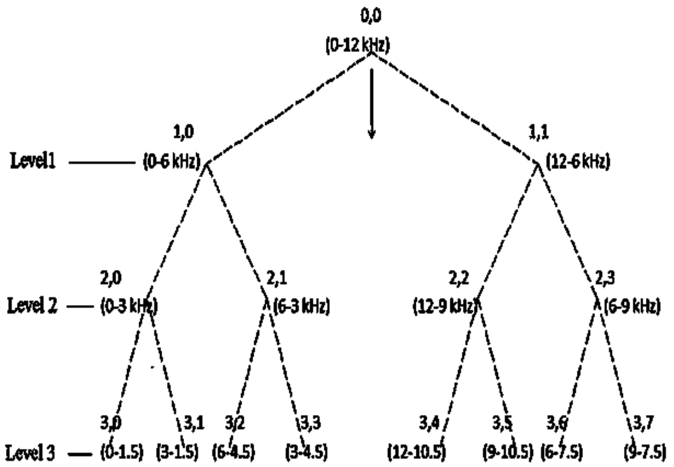

Fig. 7 Wavelet packet tree to a level of three

Wavelet Based Signal Denoising

For early fault detection, denoising and extraction of weak signals is important since the features are masked in noise. The noise is stochastic signal with broadband frequencies causing overlap with the frequency components of interest. Wavelet based denoising methods aim at increasing signal-to-noise ratio (SNR) by removing noise in the signals and highlighting the signals of interest. An orthogonal wavelet transform can compress the "energy" of the signal in a relatively small number of big coefficients, while the energy of the white noise will be dispersed throughout the transform with relatively small coefficients [39]. Wavelet threshold denoising has been widely used and it was first proposed by Donoho [40]. Wavelet decomposition of a signal is analogous to the use of filters that act as averaging filters producing approximations and others that produce details. If these details are small, they may be omitted without affecting main features of the signal. The underlying model for the noisy signal is of the form:

$$S[n] = x[n] + N_1[n] \tag{18}$$

The objective of wavelet de-noising is to suppress the additive noise $N_1[n]$ from a signal S[n] in three steps:

1. Signal decomposition: Signal S[n] is decomposed into j level of wavelet transform and coefficients are calculated.
2. Thresholding: Then the threshold is selected and the detail parts through wavelet transform are compared with the threshold and the detail parts are set to zero if less than the threshold.
3. Signal reconstruction: Finally the signal is reconstructed using the original approximation coefficients of level j and modified detail coefficients.

Generally there are two kinds of threshold functions viz., hard thresholding function and soft thresholding function. These are examples of shrinkage rules. The form of universal hard threshold function is:

$$S = \begin{cases} x & |x| \geq T \\ 0 & |x| < T \end{cases} \tag{19}$$

In hard thresholding, the coefficients whose absolute values are lower than the threshold are set to zero.
The form of universal soft threshold function is:

$$S = \begin{cases} x - T & x > T \\ 0 & |x| < T \\ x + T & x < -T \end{cases} \tag{20}$$

Soft thresholding is an extension of hard thresholding by first setting to zero the coefficients whose absolute values are lower than the threshold and then shrinking the nonzero coefficients towards zero. However, the denoising methods based on conventional thresholding rules have certain shortcomings. Some of the researchers have devised a de-noising method based on improved thresholding techniques. Yi et al. [41] have discussed de-noising performance of discrete wavelet transform (DWT) using sigmoid function-based thresholding technique by several processing parameters such as the type of wavelet, level of decomposition, thresholding method and threshold selection rules. Evaluation of performance of this method was done with denoising attributes such as signal-to-noise ratio (SNR) and the root-mean-square-error (RMSE). Lin et al. [42] introduced a specific thresholding rule which incorporates prior information of the probability density function (pdf) of the impulse based on the maximum likelihood estimation (MLE) technique for mechanical fault detection. Morlet wavelet was used as the base wavelet in de-noising. Selection of appropriate base wavelet is one of the key steps in de-noising a signal. In the last section this issue is discussed in detail. Qiu et al. [43] have compared the performance of wavelet decomposition-based de-noising and wavelet filter-based de-noising methods for analysis of defective rolling element bearings. They found wavelet filter-based method suitable for weak and impulse-like signatures and wavelet decomposition de-noising method to perform satisfactorily for smooth signals. The signal denoising results for both simulated signals and the experimental data were presented. For optimizing the shape factor of a Morlet wavelet, a criteria based on minimal Shannon entropy was used in the study. It is observed from earlier studies that energy and entropy are the decisive metrics for base wavelet selection. The distribution of vibration signal energy with scale is different for the normal rolling element bearing and the rolling element bearing with outer race or inner race fault [44]. Accordingly for bearing with defects, amplitude in the scale-wavelet spectra will differ from normal bearing. As such by comparing the scale-wavelet power spectrum, it is possible to distinguish between defect free and defective bearings and the position of the defect also.

Different studies for fault analysis related to structures, power systems and mechanical systems have made use of Shannon entropy as an important parameter [23, 45-47]. It is defined as uncertainty of a random event or the amount of information. Shannon entropy of wavelet coefficients is given as

$$S_{entropy}(n) = \sum_{i=1}^{m} p_i \log_2 p_i \tag{21}$$

where n = scale number, m = number of wavelet coefficients and pi is the energy probability distribution of the wavelet coefficients and is defined as

$$p_i = \frac{|x(n)|^2}{E(n)} \tag{22}$$

Information entropy is an information measurement which is used to locate a system under certain conditions. It is a measurement to unknown degree of a sequence and it can be used to estimate the complexity of random signal. An ordered process could be thought of as a periodic mono-frequency signal (a signal with a narrow band spectrum). A signal generated by a totally random process can be considered as representing a very disordered behavior. An appropriate wavelet is the base wavelet which minimizes the Shannon entropy of the corresponding wavelet coefficients. Ren and Sun [23] extended the wavelet transform to Shannon entropy for detecting structural damage from measured vibration signals. It is reported that the wavelet entropy-based index is a good measure of damage features and sensitive to structural local damage. Along with energy and entropy being used as wavelet selection metrics, as pointed out earlier; de-noising process also involves selection of base wavelet. As such de-noising performance attributes such as peak signal-to-noise ratio (PSNR), mean square error (MSE) and maximum error can also be investigated for base wavelet selection.

PSNR measures the ratio between the maximum possible power of a signal and the power of corrupting noise. It defines the purity of the output signal. It is given by,

$$\mathrm{PSNR} = 20 \log_{10}(\mathrm{Max}_i)/\sqrt{\mathrm{MSE}} \tag{23}$$

where Maxi is the maximum possible value of signal and MSE represents mean square error. A higher value of PSNR is good because it means that the ratio of signal to noise is higher.

The mean square error (MSE) between a signal X and an approximation Y is the squared norm of the difference divided by the number of elements in the signal. MSE is given by

$$\mathrm{MSE} = \frac{1}{N}\sum_0^N (X - Y)^2 \tag{24}$$

A lower value of MSE means lesser error.

Maximum error (MAXERR) is the maximum absolute squared deviation of the data X from the approximation Y. A denoising scheme having high PSNR, lower MSE and lower MAXERR between a signal and its approximation can be recognized as a better one.

Even though wavelet transforms have been increasingly used by many researchers for machinery fault diagnostics, the industrial applications have still not gained momentum and acceptability. The lesser prominence is mainly due to few reasons. The results obtained from wavelet transform need exploring many ramifications because often results are not straight forward. Numerous functions can be used as the wavelet basis referred throughout the thesis as mother wavelet. Functions satisfying some conditions can be designed and used as mother wavelets. Library of mother wavelets is huge and there are no unique standard guidelines for selecting the wavelet basis when multiple metrics of wavelet selection exists. In some studies, wavelet basis is adopted based on popularity and in others attempts have been made to address this problem using some quantitative selection criteria. Prabhakar et al. [28] have dealt with the detection of single and multiple ball bearing race faults by applying discrete wavelet transform. The vibration signals were decomposed up to four level using Daubechies 4 mother wavelet. Lin et al. [42] have proposed a method for wavelet threshold de-noising employing Morlet wavelet. Chebil et al. [48] have presented wavelet based analysis technique using discrete wavelet transform and the discrete wavelet packet transform using mother wavelets from Daubechies and Symlets family for the diagnosis of faults in rotating machinery.

Theoretically, even though the choice of the mother wavelet for various applications has remained ad hoc and arbitrary; it is important and critical in practice. The best mother wavelet for the situation results in perfect reconstruction and provides good localization in time and frequency. The coefficients of the wavelet transform represent how well the signal being analysed matches the base wavelet. As discussed earlier different quantitative criteria for selecting the base wavelet reported in earlier studies are maximum energy, minimum Shannon entropy and their ratio etc. Kankar et al. [49] proposed a method of selecting the best wavelet based on the ratio of maximum energy to Shannon entropy. The coefficients of wavelet transform were calculated using six different base wavelets, after calculating cyclic autocorrelation of vibration signals. The base wavelet maximizing the energy to Shannon entropy ratio was selected to extract statistical features from wavelet coefficients. They used minimum Shannon entropy criterion to select the best wavelet out of six wavelets for extracting statistical features from wavelet coefficients of raw vibration signals of bearing. After calculating Shannon entropy for each wavelet, Complex Morlet Wavelet with minimum value of entropy was selected as mother wavelet. Pandya et al. [50] have investigated the feasibility of applying wavelet packet decomposition for feature extraction of bearing vibration signals using rbio5.5 mother wavelet. They used maximum energy to minimum Shannon entropy ratio as a criterion for selecting best node of wavelet packet tree. The extracted features were used to train and test neural network for bearing fault classification.

It is concluded that selection of mother wavelet is based on the popularity in some studies. Also quantitative criteria such as maximum energy, minimum Shannon Entropy and the ratio of maximum energy to minimum Shannon entropy are decisive for selecting appropriate wavelet as reported in some studies. Wavelet based methods can be successfully applied for the analysis of bearing vibration signals heavily buried in noise. Wavelet based denoising methods rely on base wavelet. Hence in addition to energy and entropy based methods, denoising performance parameters such as peak signal to noise ratio (PSNR), mean square error (MSE) and maximum error (MAXERR) can be investigated for their appropriateness for selecting base wavelet. However, it is observed that every individual wavelet selection criteria results in different base wavelet complicating the decision making.

In this era of information technology, the field of condition monitoring has begun to incorporate technologies to assist the diagnostics and interpretation of signals with integration of Artificial Intelligence techniques such as expert systems, fuzzy logic and Neural Networks. A diagnosis method for faulty rolling element bearings based on empirical mode decomposition (EMD) energy entropy was put forward by Yu et al. [51]. Vibration signals were decomposed into a finite number of stationary intrinsic mode functions (IMFs) and then using EMD energy entropy approach, energy features extracted were fed to artificial neural network. Kumar et al. [52] used discrete wavelet transform for processing bearing vibration signals and the statistical features extracted from wavelet coefficients were fed to the artificial neural network for classification. Alexandridis and Zapranis [53] proposed Wavelet networks (WNs) as a new class of networks which have been used with great success in a wide range of applications. P.G. Kulkarni and A. D. Sahasrabudhe [54] have proposed the use benchmarks in signal denoising such as Peak signal to noise ratio (PSNR), Mean squared error (MSE), and Max error as wavelet selection criteria in addition to maximum energy and minimum Shannon entropy for selecting appropriate mother wavelet. This method is based on assigning weights to each selection criteria based on analytic hierarchy process (AHP) depending on the nature of vibration data and then finding the overall ranking of each wavelet. Mother wavelets from Daubechies, Symlet, Coiflet, and Bior families are investigated and the best mother wavelets proposed by the weighting schemes are further used for processing vibration signals using a multiresolution analysis. This methodology is successfully implemented for assessing health of bearings of critical subsystem of a lathe machine tool. The new wavelet selection strategy may be implemented with equal success for health assessment of a broad range of machine tools such as CNC lathes, milling machines, machining centers, and other delicate machine tools.

With the advent in technology, researchers have focused on application of intelligent fault diagnosis systems using machine learning and neural network. In the next section, the work carried on this topic is discussed.

V. Artificial Intelligence Methods for Fault Diagnosis

Due to the variability and richness of the response signals, it is almost impossible to recognize fault patterns directly. Therefore, a common fault diagnosis system often consists of three key steps: data processing, feature extraction and fault diagnosis [55]. Fault diagnosis of rotating machinery is a technique of fault detection, isolation and identification. This information is useful to know about the operational condition of the equipment [56].

There are mainly three types of fault diagnosis:

a) Determining whether there is fault in the equipment or not

b) Finding the exact position of the fault

c) Predicting the trend of fault development.

For pattern recognition problem of rotating machinery Artificial intelligent has attracted great attention in the recent years and it has also shown promising results in the fault recognition in rotating machinery [57]. Most common intelligent fault diagnosis systems are built based on the preprocessing by feature extraction algorithms to transform the input patterns so that they can be represented by low-dimensional feature vectors for easier match and comparison. Then, the feature vectors are used as the input of AI techniques for fault recognition. The step of fault recognition amounts to mapping the information obtained in the feature space to machine faults in the fault space. Numerous AI tools or techniques have been used, including convex optimization, mathematical optimization, as well as classification-, statistical learning- and probability-based methods. Specifically, classifiers and statistical learning methods have been widely used in fault diagnosis of rotating machinery, that includes, k-nearest neighbor (k-NN) algorithms [58], Bayesian classifier [59], support vector machine (SVM) [60] and artificial neural network (ANN) [61]. Most recently, deep learning approaches have also begun to be applied in the field of fault diagnosis [62].

Support vector Machines (SVM)

Support Vector Machines are one of the most popular classification algorithms. SVM is a supervised type of machine learning algorithm. SVM can be used for both classification and regression challenges. However, it is mostly used for the classification problems. The objective of the SVM algorithm is to create the best line or decision boundary that can segregate n-dimensional space into classes so that the new data point can be easily put in the correct category in the future. Example of Support vector machine algorithm is shown in the Fig. 8. This best decision boundary is called a hyper plane. In the SVM algorithm, suppose the number of features extracted is n then each data item is plotted in n dimensional space with the value of each feature being the value of a particular coordinate. Then classification can be performed by finding the hyper plane that differentiates the two classes very well. SVM chooses the extreme points/vectors that help in creating the hyperplane. These extreme cases are called as support vectors, and hence algorithm is termed as Support Vector Machine. Support Vectors are simply the co-ordinates of individual observation. SVM has an excellent performance in generalization with small training data. SVM is used to separate two classes to find support vectors that defines the bounding plane. The number of support vectors increases with the complexity of the problem. For more than 10 classes SVM is less good. SVM tends to generalize well even with a limited amount of training data. To select the kernel function parameters is very difficult. It is less efficient in a case of lot of data, because number of support vectors increases with the complexity of the problem [63]. SVM algorithm was proposed for fault diagnosis of the rotational unbalance in the rotor. Several situation of unbalance faults were detected successfully. The SVM algorithm has a practical signification for the machine learning in the case of a small number of samples [64]. Lie You et al [65] have proposed a novel fault diagnosis model for vertical axial flow pump, which extracts features by combining vibration severity, dyadic wavelet energy time-spectrum, and coefficient power spectrum of the maximum wavelet energy level (VWC) at the feature extraction stage. At the stage of fault classification, a support vector machine (SVM) is designed based on the modified shuffled frog-leaping algorithm (MSFLA) for the accurate classifying machinery fault method. Shaojiang dong et al. [66] have explained a novel method to solve the rotating machinery fault diagnosis, which is based on principal components analysis (PCA) to extract the characteristic features and the Morlet kernel support vector machine (MSVM) to achieve the fault classification. The Morlet kernel can effectively improve the recognition accuracy of SVM. Xiaochen Zhang et al. [67] have proposed a method based on fast clustering algorithm (FCA) and support vector machine (SVM) to diagnose rotating machinery fault for imbalanced data. Chenxi Wu et al. [68] employed based on continuous wavelet transform (CWT) and support vector machine (SVM) for the diagnosis of bearing faults. They have presented a method for selection of mother wavelet. They have reported higher accuracy in fault diagnosis with this method.

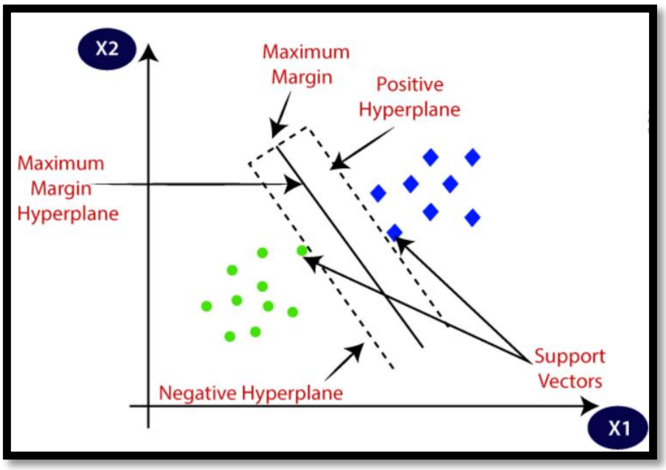

Fig.8 Support vector machine algorithm

T Praveenkumar et al. [69] have carried out the fault diagnosis of gear box by using statistical features extracted from the acquired vibration signals. The extracted features were given as an input to the support vector machine (SVM) for fault identification. The Performance of the fault identification system using vibration signals are discussed and compared Support Vector Machine shows better classification ability in identification of a various faults in the gearbox and it can be used for automated fault diagnosis.

Artificial Neuron Networks (ANNs)

Neural network can be defined as a computing system made up of a number of simple, highly interconnected processing elements, which process information by their dynamic state response to external inputs. Artificial Neural Network as computational model that is inspired by the way biological neural networks in the human brain process information.

There are three components in ANNs. Input layer, hidden layer and output layer with some activation function and learning rules. Each layer is comprised of n nodes (n P 1) and each node in any layer is connected to all the nodes in the neighbouring layers. Each node can also be connected to a constant number which is called bias. These connections have their individual weights which are called synaptic weights and are multiplied to the node values of the previous layer. Input and output data dimensions of the ANN determine the number of nodes in the input and output layers, respectively, but the number of hidden layers and their nodes is determined heuristically and that is the most important part in ANNs accuracy of results depends on this. A single layer perceptron as shown in Fig.9 is a feed-forward network based on a threshold transfer function. SLP is the simplest type of artificial neural networks and can only classify linearly separable cases with a binary target (1, 0).

Activation function of a node defines the output of that node given an input or set of inputs. Every activation function (or transfer function) takes a single number and performs a certain fixed mathematical operation on it. Sigmoid, Tanh, ReLU are some examples of activation functions. The *learning rule* is a rule or an algorithm which modifies the parameters of the neural network, in order for a given input to the network to produce a favoured output. This *learning* process typically amounts to modifying the weights and thresholds.

There are many classes of neural networks viz. Artificial Neural Network (ANN), Convolutional Neural Network (CNN), Recurrent Neural Network (RNN) etc. Artificial Neural Network (ANN) is a very broad term that encompasses any form of Deep Learning model. ANNs can be either shallow or deep. They are called shallow when they have only one hidden layer (i.e. one layer between input and output). They are called deep when hidden layers are more than one (what people implement most of the time). This is where the expression Deep Neural Network (DNN) comes.

Convolutional Neural Network (CNN) are designed specifically for computer vision (they are sometimes applied elsewhere though). The CNN are deep neural networks that focus mainly on image processing and are excellent for pattern recognition. In addition, it is one of the best methods for classification. CNN automatically obtain the characteristics of the images by means of convolutional filters, which makes them a tool with a great capacity to learn characteristics in a robust and sensitive way. Their name come from convolutional layers: they are different from standard (dense) layers of canonical ANNs, and they have been invented to receive and process pixel data. Recurrent Neural Network (RNN) are the "time series version" of ANNs. They are meant to process sequences of data.

A feed forward neural network is an artificial neural network where connections between the units do not form a cycles or loops in the network. In this network, the information moves in only one direction, forward, from the input layers, through the hidden layer (for single layer perceptron no hidden layer) and to the output layers or nodes. (Fig. 9)

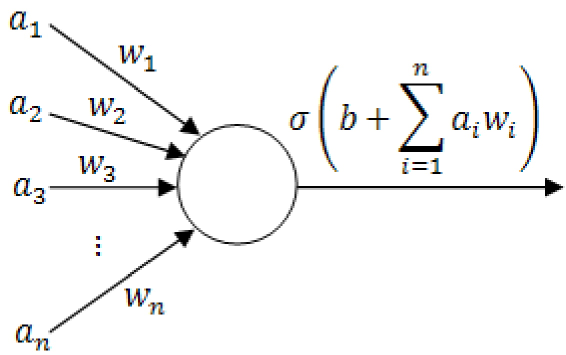

Fig. 9 Single-layer Perceptron

Multi-layer perceptron (MLP) consists of multiple layers of computational units as shown in the Fig. 10, usually interconnected in a feed-forward way. Each neuron in one layer has directed connections to the neurons of the subsequent layer. In many applications the units of these networks apply a sigmoid function as an activation function. MLP are very more useful and one good reason is that, they are able to learn non-linear representations.
Convolutional Neural Networks (CNNs) are very similar to ordinary Neural Networks, they are made up of neurons that have learnable weights and biases. In convolutional neural network (CNN, or ConvNet or shift invariant or space invariant) the unit connectivity pattern is inspired by the organization of the visual cortex as shown in the Fig.11. Units respond to stimuli in a restricted region of space known as the receptive field. Receptive fields partially overlap, over-covering the entire visual field. Unit response can be approximated mathematically by a convolution operation. They are variations of multilayer perceptrons that use minimal pre-processing. Their wide applications is in image and video recognition, recommender systems and natural language processing. CNNs requires large data to train on.

In recurrent neural network (RNN), connections between units form a directed cycle (they propagate data forward, but also backwards, from later processing stages to earlier stages). This allows it to exhibit dynamic temporal behavior. Unlike feed forward neural networks, RNNs can use their internal memory to process arbitrary sequences of inputs. This makes them applicable to tasks such as unsegmented, connected handwriting recognition, speech recognition and other general sequence processors. CNNs are feed-forward Artificial Neural Networks (ANNs) with alternating convolutional and subsampling layers. Deep 2D CNNs with many hidden layers and millions of parameters have the ability to learn complex objects and patterns providing that they can be trained on a massive size visual database with ground-truth labels. With a proper training, this unique ability makes them the primary tool for various engineering applications for 2D signals such as images and video frames. Yet, this may not be a viable option in numerous applications over 1D signals especially when the training data is scarce or application-specific. To address this issue, 1D CNNs have recently been proposed and immediately achieved the state-of-the-art performance levels in several applications such as personalized biomedical data classification and early diagnosis, structural health monitoring, anomaly detection and identification in power electronics and motor-fault detection.

Another major advantage is that a real-time and low-cost hardware implementation is feasible due to the simple and compact configuration of 1D CNNs that perform only 1D convolutions (scalar multiplications and additions). This paper presents a comprehensive review of the general architecture and principals of 1D CNNs along with their major engineering applications, especially focused on the recent progress in this field. Their state-of-the-art performance is highlighted concluding with their unique properties. The benchmark datasets and the principal 1D CNN software used in those applications are also publically shared in a dedicated website [70]. Tang et al [71] have used intelligent fault diagnosis techniques for rotary machinery based on with deep neural network. As a common DNN with special structure, deep convolutional neural network is of great concern in intelligent fault diagnosis due to its advantages in processing nonlinear problems for rotary machinery.

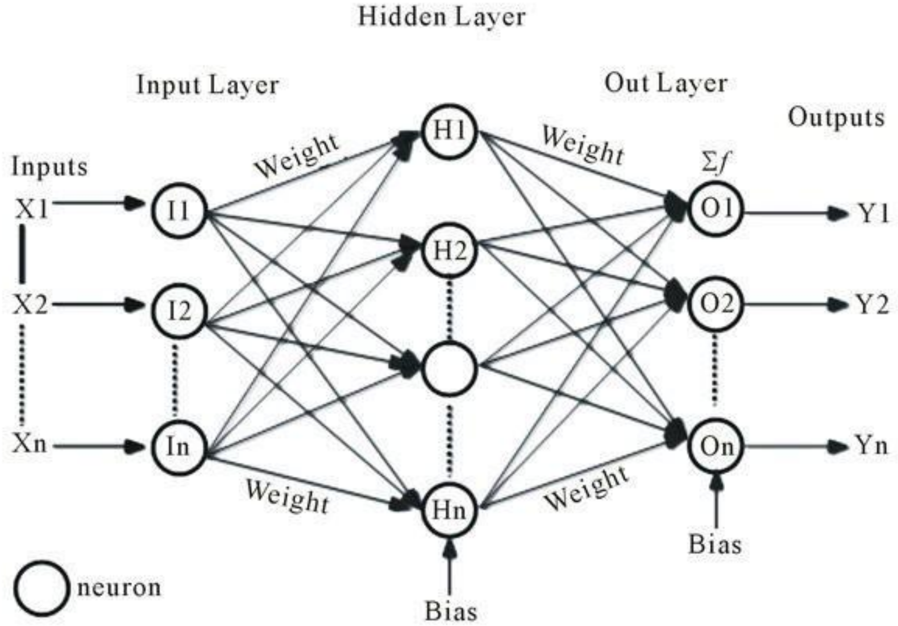

Fig. 10 Multi-Layer Perceptron

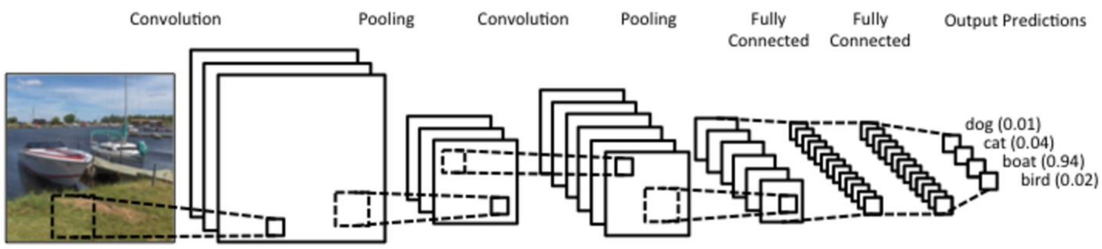

Fig.11 CNN for image classification

The DNN is successfully used in different applications including image processing, speech recognition and audio processing [72]. Owing to the advantages of DNN in thorough learning capability, it is valuable to explore the feature mining and intelligent diagnosis methods based on DNN in research on mechanical failure [73- 76]. In this method Local connection means each neuron in the convolutional layer is only connected to the neuron in a local window in the next layer, and every kernel is viewed as a small local window with a certain stride. Weights sharing can be understood that one convolutional kernel can only capture a kind of specific local feature from the input data. Luo et al. [77] have proposed Variable predictive model-based class (VPMCD) for the fault diagnosis of rotating machinery. The fault diagnosis process is essentially a class discrimination problem. However, traditional class discrimination methods such as SVM and ANN fail to capitalize the interactions among the feature variables. VPMCD can adequately use the interactions. But the feature extraction and selection will greatly affect the accuracy and stability of VPMCD classifier. Aiming at the nonstationary characteristics of vibration signal from rotating machinery with local fault, singular value decomposition (SVD) technique based local characteristic-scale decomposition (LCD) was developed to extract the feature variables. Subsequently, combining artificial neural net (ANN) and mean impact value (MIV), ANN-MIV as a kind of feature selection approach was proposed to select more suitable feature variables as input vector of VPMCD classifier. Chan et al. [78] has proposed feature inherited hierarchical convolution neural network (FI-HCNN) to improve motor fault severity estimation. The main novelty of the proposed FI-HCNN is the special inherited structure between the hierarchy; the severity estimation part utilizes the latent features to exploit the fault-related representations in the fault diagnosis task. FI-HCNN can improve the accuracy of the fault severity estimation because the level-specific abstraction is supported by the latent features. Experimental studies of mechanical motor faults, including eccentricity, broken rotor bars, and unbalanced conditions are used to corroborate the high performance of FI-HCNN. Yong et al. [79] have proposed a novel method for the diagnosis of bearing faults using hierarchical multitask convolution neural networks (HMCNNs). This method focuses on the relationship between fault location, fault type, and fault severity. HMCNN model includes a main task and multiple subtasks. In the HMCNN model, a weighted probability is used to reduce the classification error propagation among multitasks to improve the fault diagnosis accuracy. ZhiQiang et al. [80] have presented an implementation of deep learning algorithm convolutional neural network (CNN) used for fault identification and classification in gearboxes. Different combinations of condition patterns based on some basic fault conditions are considered. 20 test cases with different combinations of condition patterns are used, where each test case includes 12 combinations of different basic condition patterns. Vibration signals are pre-processed using statistical measures from the time domain signal such as standard deviation, skewness, and kurtosis. In the frequency domain, the spectrum obtained with FFT is divided into multiple bands, and the root mean square (RMS) value is calculated for each one so the energy maintains its shape at the spectrum peaks. The achieved accuracy indicates that the proposed approach is highly reliable and applicable in fault diagnosis of industrial reciprocating machinery. Dong et al. [81] have proposed novel method of fault diagnosis based on convolutional neural network (CNN), discrete wavelet transform (DWT), and singular value decomposition (SVD). CNN is used to extract features of shaft orbit images, DWT is used to transform the denoised swing signal of rotating machinery, and the wavelet decomposition coefficients of each branch of the signal are obtained by the transformation. To effectively identify the fault classes of rotating machinery under noise interference, an efficient fault diagnosis method without additional denoising procedures is proposed. First, a one-dimensional deep residual shrinkage network, which directly takes the raw vibration signals contaminated by noise as input, is developed to realize end-to-end fault diagnosis. An adaptive batch normalization algorithm (AdaBN) is introduced into the diagnosis model to enhance the adaptability to noise. [82]. Deep 2D CNNs with many hidden layers and millions of parameters have the ability to learn complex objects and patterns providing that they can be trained on a massive size visual database with ground-truth labels. With a proper training, this unique ability makes them the primary tool for various engineering applications for 2D signals such as images and video frames. Yet, this may not be a viable option in numerous applications over 1D signals especially when the training data is scarce or application-specific. To address this issue, 1D CNNs have recently been proposed and immediately achieved the state-of-the-art performance levels in several applications such as personalized biomedical data classification and early diagnosis, structural health monitoring, anomaly detection and identification in power electronics and motor-fault detection. Another major advantage is that a real-time and low-cost hardware implementation is feasible due to the simple and compact configuration of 1D CNNs that perform only 1D convolutions (scalar multiplications and additions). Zhiqiang Chen et al. [83] presented a study of deep neural networks for fault diagnosis in gearbox. Four classic deep neural networks (Auto-encoders, Restricted Boltzmann Machines, Deep Boltzmann Machines and Deep Belief Networks) were employed as the classifier to classify and identify the fault conditions of gearbox. It was concluded that Multi-layer feed-forward neural network with one or two hidden layers performs better than deeper net architectures for gearbox fault diagnosis. It was observed that the deep learning algorithms, RBM, DBM, DBN and SAE, were efficient, reliable and robust in gearbox fault diagnosis. Israel £. Alguihdigue and Robert E. Uhrig [84] have presented the work on the design of a vibration monitoring methodology based on neural network technology using two neural networks algorithms, first the Recirculation algorithm for data compression and second the back propagation algorithm to perform the actual classification of the patterns. It is concluded that to implement reliable monitoring systems using neural networks, it is best to utilize multiple independent networks to address several phases of the problem, then to design a large network capable of performing all analysis. Luis A. Pinedo- Sanchez et al. [85] have proposed a method based on **Convolutional Neural Networks (CNN)** to estimate the level of wear in roller bearings in each of its elements, inner race, outer race and rolling element. They found a CNN model based on the AlexNet architecture to be an effective tool to classify the wear level and diagnose the rotating system. Wenliao Du et al. [86] have developed a method based on dual-tree complex wavelet transform based stacked sparse autoencoder for intelligent fault diagnosis of rotating machinery. They concluded that the developed method can accommodate changing working conditions, be free of manual feature extraction, and perform better than the existing intelligent diagnosis methods. Shaojiang Dong et al. [87] implemented a method based on the k-nearest neighbor classification algorithm is used for completing the fault diagnosis of rolling bearing under variable working conditions. In order to solve the problem of low diagnosis results of traditional bearing fault diagnosis methods under different working conditions, an unsupervised deep learning algorithm combined with feature transfer learning was proposed. Haedong Jeong et al. [88] an autonomous orbit pattern recognition algorithm using the deep learning method on shaft orbit shape images. In details, the convolutional neural network is implemented to construct weights between neurons and to generate the entire structure of the neural network. This was done with an objective to identify rotating machinery dynamics and status. Chih-Hao Chena et al. [89] have presented a study for the fault diagnosis procedure for rotating machinery using the wavelet packets-fractal technology and a radial basis function neural network. The faults of rotating machinery considered in this study include imbalance, misalignment, looseness and imbalance combined with misalignment conditions. It was found that the wavelet packets decomposition can accurately decompose vibration signals into various perpendicular frequency bands without losing the characteristics of the measured vibration signals. Chuan Li et al. [90] have proposed deep statistical feature learning for vibration measurement to diagnose fault patterns in rotating machinery. The statistical feature set was first extracted from the time, frequency, and time-frequency domains of the vibration signals. It was concluded that deep statistical feature learning is capable of classifying fault patterns at higher rates than other models.

VI. Conclusion

With the increasing complexity of mechanical structures, it is increasingly important to monitor and diagnose the condition of rotating machinery. In many cases, the vibration signal and shaft orbit are important features that reflect the state of mechanical equipment. Therefore, an efficient feature extraction and fault diagnosis method plays a significant role in the operation management and condition monitoring of mechanical equipment. For the fault diagnosis of rotating machinery intelligent systems are used for more efficient and accurate results. But a single method cannot give exact results for that there must be a combination of different methods based on data available and output desired in a specific manner. For feature classification no of classifiers are there with different algorithms. And for deep learning different neural networks are proposed for application based and particular condition based. Fault diagnosis of rotating machinery is a predominant research area to get the novel approach for diagnosis of fault by blending of different methods. The useful life prediction is ongoing research area.

References

[1]. Aherwar, A. An investigation on gearbox fault detection using vibration analysis techniques: A review. Australian Journal of Mechanical Engineering. 2012; 10(2): 169-184.

[2]. Loutas TH, Roulias D, Pauly E, Kostopoulos V. The combined use of vibration, acoustic emission and oil debris on-line monitoring towards a more effective condition monitoring of rotating machinery. Mechanical Systems and Signal Processing. 2011; 25:1339–1352.

[3]. Emmanuel Resendiz-Ochoa, Juan J Saucedo-Dorantes, Juan P Benitez-Rangel, Roque A, Osornio-Rios and Luis A, Morales-Hernandez. Novel Methodology for Condition Monitoring of Gear Wear Using Supervised Learning and Infrared Thermography. Appl. Sci. 2020; 10, 506; doi: 10.3390/app10020506, MDPI.

[4]. Wei Yu, Yuqing Li, Minqiang Xu and Wenhu Huang. A Review of Early Fault Diagnosis Approaches and Their Applications in Rotating Machinery. Entropy 2019, 21, 409; doi: 10.3390/e21040409, MDPI.

[5]. Xuefeng CHE N, Shibin WANG, Baijie QIAO, Qiang CHEN. Basic research on machinery fault diagnostics: Past, present, and future trends. Front. Mech. Eng. 2018, 13(2): 264–291.

[6]. Kulkarni PG, Sahasrabudhe AD. A Theoretical Model For Studying Vibrations of Ball Bearing With Localised Defects On Inner Race Using Cubic Hermite Spline. 2015 International Conference on Industrial Instrumentation and Control (ICIC), IEEE.

[7]. Kulkarni PG and Sahasrabudhe AD. A dynamic model of ball bearing for simulating localized defects on outer race using cubic hermite spline, Journal of Mechanical Science and Technology. 2014; 28 (9):3433-3442.

[8]. Kulkarni PG, N. G. Jaiswal, Ami R. Barot. Analysis of Vibration Signals of Rolling Element Bearings with Localized Defects. IJMER 2020; 10(7):41-49.

[9]. Goyal Deepam, Vanraj BS, Pabla SS, Dhami. Condition Monitoring Parameters for Fault Diagnosis of Fixed Axis Gearbox: A Review. Arch Computat Methods Eng. 2017; 24:543–556.

[10]. Ognjanovic M. Progressive Gear Teeth Wear and Failure Probability Modelling. Tribology in industry. 2004; 26(3&4).

[11]. Choy FK, Polyshchuk V, Zakrajsek JJ, Handschuh RF and Townsendi DP. Analysis of the effects of surface pitting and wear on the vibration of a gear transmission system. Tribology International. 1996; 29(1): 71-83.

[12]. Tandon N and Choudhury A. An analytical model for the prediction of the vibration response of rolling element bearings due to a localized defect. Journal of Sound and Vibration. 1997; 205(3): 275–292.

[13]. White MF. Simulation and analysis of machinery fault signals. Journal of Sound and Vibration. 1984; 93(1):95-116.

[14]. McFadden PD and Smith JD. The vibration produced by multiple point defects in a rolling element bearing. Journal of Sound and Vibration. 1985; 98(2): 263–273.

[15]. Su YT and Lin SJ. On initial fault detection of a tapered roller bearing: Frequency domain analysis. Journal of Sound and Vibration. 1992; 155(1):75-84.

[16]. Patel VN, Tandon N, Pandey RK. A dynamic model for vibration studies of deep groove ball bearings considering single and multiple defects in races. Journal of Tribology. 2010; 132 (4):041101-1-10.

[17]. Deore KS, Khandekar MA. Bearing fault detection in induction motor using time domain analysis. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering. 2014; 3(7): 10702-10707.

[18]. Shakya P, Darpe AK and Kulkarni MS. Vibration-based fault diagnosis in rolling element bearings: ranking of various time, frequency and time-frequency domain data-based damage identification parameters. International Journal of Condition Monitoring. 2013; 3(2):53–62.
[19]. Dyer D and Stewart RM. Detection of rolling element bearing damage by statistical vibration analysis. ASME Journal of Mechanical Design. 1978; 100(2):229-235.
[20]. B. K. N. Rao, Handbook of condition monitoring (Elsevier Science ltd 1996).
[21]. Wang X, Makis V, Yang M. A wavelet approach to fault diagnosis of a gearbox under varying load conditions. Journal of Sound and Vibration. 2010; 329 (9):1570-1585.
[22]. Bendjama H, Bouhouche S, Boucherit MS. Application of wavelet transform for fault diagnosis in rotating machinery. International Journal of Machine Learning and Computing. 2012; 2(1): 82-87.
[23]. Ren WX, Sun ZS. Structural damage identification by using wavelet entropy. Engineering Structures. 2008; 30 (10): 2840-2849.
[24]. Tiwari R, Bordoloi DJ, Bansal S and Sahu S. Application of wavelet analysis in multi-class fault diagnosis of gear using SVM. International Journal of Condition Monitoring and Diagnostic Engineering. 2013; 16(3):17-24.
[25]. Al-Badour F, Sunar M, Cheded L. Vibration analysis of rotating machinery using time-frequency analysis and wavelet techniques. Mechanical Systems and Signal Processing. 2011; 25 (6): 2083-2101.
[26]. Peng ZK, Chu FL. Application of the wavelet transform in machine condition monitoring and fault diagnostics: a review with bibliography. Mechanical Systems and Signal Processing. 2004; 18:199-221.
[27]. Kulkarni Pravin and Barot Ami. A Wavelet Based Multi-resolution Technique for Analysis of Vibration Signals. International Journal of Science Technology & Engineering. 2020; 7(4): 2349-784
[28]. Djebala A, Ouelaa N, Hamzaoui N, Chaabi L. Detecting mechanical failures inducing periodical shocks by wavelet multiresolution analysis. Application to rolling bearings faults diagnosis. MECHANIKA. 2006 ;(58): 44-51.
[29]. Al-Badour F, Sunar M, Cheded L. Vibration analysis of rotating machinery using time-frequency analysis and wavelet techniques. Mechanical Systems and Signal Processing. 2011; 25 (6): 2083-2101.
[30]. Castro JMA, Lopez MEB, Ocampo JC, Szwdowicz D, Oliver MA. Dynamic response of antifriction bearings via minimum Shannon entropy. Proceedings of the XIth International Congress and Exposition. 2008; Society for Experimental Mechanics Inc.
[31]. Soman KP, Ramachandran KI. Insight into Wavelets - From Theory to Practice. 2005; 2nd Edition, Prentice Hall of India Private Limited.
[32]. Nikolaou NG, Antoniadis IA. Rolling element bearing fault diagnosis using wavelet packets. NDT& E International. 2002; 35:197-205.
[33]. Prabhakar S, Mohanty AR, Sekhar AS. Application of discrete wavelet transform for detection of ball bearing race faults. Tribology International. 2002; 35: 793–800.
[34]. Kulkarni PG, Sahasrabudhe AD. Application of wavelet transform for fault diagnosis of rolling element bearings. International Journal of Scientific & Technology Research. 2013; 2(4):2277-8616.
[35]. Liu B. Selection of wavelet packet basis for rotating machinery fault diagnosis. Journal of Sound and Vibration. 2005; 284: 567-582.
[36]. Wei Z, Gao J, Zhong X, Jiang Z, Ma B. Incipient fault diagnosis of rolling element bearing based on wavelet packet transform and energy operator. WSEAS Transactions on Systems. 2011; 3(10): 81-90.
[37]. Learned RE and Willsky AS. A wavelet packet approach to transient signal classification. Applied and Computational Harmonic Analysis. 1995; 2: 265-278.
[38]. Ekici S, Yildirim S, Poyraz M. Energy and entropy-based feature extraction for locating fault on transmission lines by using neural network and wavelet packet decomposition. Expert Systems with Applications. 2008; 34: 2937-2944.
[39]. Peng ZK, Chu FL. Application of the wavelet transform in machine condition monitoring and fault diagnostics: a review with bibliography. Mechanical Systems and Signal Processing. 2004; 8: 199-221.
[40]. Donoho DL. De-noising by soft-thresholding, IEEE Transactions on Information Theory. 1995; 41(3): 613-627.
[41]. Yi TH, Li HN and Zhao XY. Noise smoothing for structural vibration test signals using an improved wavelet thresholding technique. Sensors. 2012; 12(8)
: 11205-11220.
[42]. Lin J, Zuo MJ, Fyfe KR. Mechanical fault detection based on the wavelet de-noising technique. Journal of Vibration and Acoustics. 2004; 126: 9-16.
[43]. Qiu H, Lee J, Lin J, Yu G. Wavelet filter-based weak signature detection method and its application on rolling element bearing prognostics. Journal of Sound and Vibration. 2006; 289: 1066-1090.
[44]. Junsheng C, Dejie Y, Yu Y. Application of an impulse response wavelet to fault diagnosis of rolling bearings. Mechanical Systems and Signal Processing. 2007; 21: 920-929.
[45]. Chen X, Gao Z. Data processing based on wavelet analysis in structure health monitoring system. Journal of Computers. 2011; 6(12): 2686-2691.
[46]. S. EI Safty, A. EI-Zonkoly. Applying wavelet entropy principle in fault classification. Journal of Electrical Power and Energy Systems. 2009; 31:604-607.
[47]. Kankar PK, Sharma SC, Harsha SP. Fault diagnosis of rolling element bearing using cyclic autocorrelation and wavelet transform. Neurocomputing. 2013; 110: 9-17.
[48]. Chebil J, Noel G, Mesbah M, Deriche M. Wavelet decomposition for the detection and diagnosis of faults in rolling element bearings. Jordan Journal of Mechanical and Industrial Engineering. 2009; 3(4): 260-267.
[49]. Bhavaraju KM, Kankar PK, Sharma SC, Harsha SP. A comparative study on bearings faults classification by artificial neural networks and self-organising maps using wavelets. International Journal of Engineering Science and Technology. 2010; 2(5):1001-1008.
[50]. Pandya DH, Upadhyay SH, Harsha SP. ANN based fault diagnosis of rolling element bearing using time-frequency domain feature, International Journal of Engineering Science and Technology. 2012; 4(6): 2878-2886.
[51]. Yu Y, Dejie Y, Junsheng C. A roller bearing fault diagnosis method based on EMD energy entropy and ANN. Journal of Sound and Vibration. 2006; 294: 269-277.
[52]. Kumar HS, Pai PS, Sriram NS, Vijay GS. ANN based evaluation of performance of wavelet transform for condition monitoring of rolling element bearing. Procedia Engineering. 2013; 64: 805-814.
[53]. Alexandridis AK, Zapranis AD, and Wavelet neural networks: A practical guide, Neural Networks. 2013; 42: 1–27.
[54]. Kulkarni PG, Sahasrabudhe AD. Investigations on mother wavelet selection for health assessment of lathe bearings, The International Journal of Advanced Manufacturing Technology. 2017; 90: 3317-3331.
[55]. Yang H, Mathew J, Ma L. Fault diagnosis of rolling element bearings using basis pursuit. Mech. Syst. Sign. Process. 2005; 19 (2):341–356.
[56]. Jardine AK, Lin D, Banjevic D. A review on machinery diagnostics and prognostics implementing condition-based maintenance, Mech. Syst. Sign. Process. 2006; 20 (7):1483–1510.
[57]. Ruonan Liu, Boyuan Yang, Enrico Zio, Xuefeng Chen. Artificial intelligence for fault diagnosis of rotating machinery: A review. Mechanical Systems and Signal Processing. 2018; 108: 33–47.

[58]. Wang D. K-nearest neighbors based methods for identification of different gear crack levels under different motor speeds and loads: revisited. Mech. Syst. Sign. Process. 2016; 70: 201–208.

[59]. Baraldi P, Podofillini L, Mkrtchyan L, Zio E, Dang VN. Comparing the treatment of uncertainty in bayesian networks and fuzzy expert systems used for a human reliability analysis application. Reliab. Eng. Syst. Saf. 2015; 138:176–193.

[60]. Vapnik V. The Nature of Statistical Learning Theory, Springer Science & Business Media, 2013.

[61]. Haykin S. Neural Network, A comprehensive foundation. Pearson Education 2004.

[62]. Lei Y, Jia F, Lin J, Xing S, Ding S. An intelligent fault diagnosis method using unsupervised feature learning towards mechanical big data. 2016; 63(5):3137-3147.

[63]. Ndeye Lo, Jean-Marie Flaus, Olivier Adrot. Review of Machine Learning Approaches in Fault Diagnosis applied to IoT System. International Conference on Control, Automation and Diagnosis ICCAD'19, Jul 2019, Grenoble, France. HAL

[64]. Allan Alves Pinheiro, Iago Modesto Brandao and Cesar da Costa.Vibration Analysis of Rotary Machines Using Machine Learning Techniques. European Journal of Engineering Research and Science. 2019; 4(2).

[65]. Lei You, Wenjie Fan, Zongwen Li, Ying Liang, Miao Fang, and Jin Wang. A Fault Diagnosis Model for Rotating Machinery Using VWC and MSFLA-SVM Based on Vibration Signal Analysis. Hindawi, Shock and Vibration.2019.

[66]. Shaojiang Dong, Dihua Sun, Baoping Tang, Zhenyuan Gao, Wentao Yu, and Ming Xia. A Fault Diagnosis Method for Rotating Machinery Based on PCA and Morlet Kernel SVM. Hindawi Publishing Corporation. Mathematical Problems in Engineering Volume 2014.

[67]. Xiaochen Zhang, Dongxiang Jiang, Te Han, Nanfei Wang, Wenguang Yang, and Yizhou Yang. Rotating Machinery Fault Diagnosis for Imbalanced Data Based on Fast Clustering Algorithm and Support Vector Machine. Hindawi Journal of Sensors.2017.

[68]. Chenxi Wu, Tefang Chen, Rong Jiang, Liwei Ning, Zheng Jiang. A novel approach to wavelet selection and tree kernel construction for diagnosis of rolling element bearing fault. Journal of Intell Manuf. 2017; 28:1847–1858.

[69]. Praveenkumar T, Saimuruganb M, Krishnakumarc P, Ramachandrand KI. Fault diagnosis of automobile gearbox based on machine learning techniques. Procedia Engineering. 2014; 97: 2092 – 2098

[70]. Serkan Kiranyaz, Onur Avci, Osama Abdeljaber, Turker Ince, Moncef Gabbouj, Daniel J. Inman. D Convolutional Neural Networks and Applications – A Survey "

[71]. Shengnan Tang, Shouqi Yuan, and Yong Zhu. Convolutional Neural Network in Intelligent Fault Diagnosis Toward Rotatory Machinery, IEEE Access.

[72]. Venkateswara H, Chakraborty S, and Panchanathan S. Deep-learning systems for domain adaptation in computer vision. IEEE Signal Processing. 2017; 34(6):117-129.

[73]. Zhang L, Zuo W and Zhang D. LSDT: Latent sparse domain transfer learning for visual adaptation. IEEE Trans. Image Processing. 2016;25(3):1177-1191.

[74]. Jia F, Lei Y, Lin J, Zhou X, and Lu N. Deep neural networks: A promising tool for fault characteristic mining and intelligent diagnosis of rotating machinery with massive data. Mech. Syst. Signal Processing. 2016; 72-73:303-315.

[75]. Wang Z et al. Fully memristive neural networks for pattern classification with unsupervised learning. Nature Electron. 2018;1(2):137-145.

[76]. Peng X. A spheres-based support vector machine for pattern classification. Neural Comput. Appl. 2019; 31: 379-396.

[77]. Songrong Luo, Junsheng Cheng, and Kexiang Wei. A Fault Diagnosis Model Based on LCD-SVD-ANN-MIV and VPMCD for Rotating Machinery. Hindawi Publishing Corporation Shock and Vibration. 2016.

[78]. Chan Hee Park, Hyunjae Kim, Junmin Lee, Giljun Ahn, Myeongbaek Youn, Byeng D. A Feature Inherited Hierarchical Convolutional Neural Network (FI‑ HCNN) for Motor Fault Severity Estimation Using Stator Current Signals. International Journal of Precision Engineering and Manufacturing-Green Technology. 2020.

[79]. Yong-Zhi Liu, Yi-Sheng Zou, Yu-Liang Jiang, Hui Yu and Guo-Fu Ding. A Novel Method for Diagnosis of Bearing Fault Using Hierarchical Multitasks Convolutional Neural Networks.Shock and Vibration.2020.

[80]. Zhi Qiang Chen, Chuan Li, and René-Vinicio Sanchez. Gearbox Fault Identification and Classification with Convolutional Neural Networks, Shock and Vibration. 2015.

[81]. Dong Liu, Xu Lai, Zhihuai Xiao, Dong Liu, Xiao Hu and Pei Zhang. Fault Diagnosis of Rotating Machinery Based on Convolutional Neural Network and Singular Value Decomposition, Shock and Vibration.2020.

[82]. Jingli Yang, Tianyu Gao, Shouda Jiang, Shijie Li and Qing Tang. Fault Diagnosis of Rotating Machinery Based on One-Dimensional Deep Residual Shrinkage Network with a Wide Convolution Layer. Hindawi, Shock and Vibration.2020.

[83] Zhiqiang Chen, Xudong Chen, Chuan Li, René-Vinicio Sanchez, Huafeng Qin. Vibration-based gearbox fault diagnosis using deep neural networks. Journal of Vibroengineering. 2017; 19(4): 2475-2496.

[84] Israel £. Alguihdigue and Robert E. Uhrig. Vibration monitoring with artificial neural networks. Proceedings of the SMORN VI symposium on nuclear reactor surveillance and diagnostics Gatlinburg, TN.1991.

[85] Luis A, Pinedo‑ Sanchez Diego A, Mercado‑ Ravell1, Carlos A, Carballo‑ Monsivais. Vibration analysis in bearings for failure prevention using CNN. Journal of the Brazilian Society of Mechanical Sciences and Engineering, 2020.

[86]. Wenliao Du, Shuangyuan Wang, Xiaoyun Gong, Hongchao Wang, Xingyan Yao, and Michael Pecht. Translation Invariance-Based Deep Learning for Rotating Machinery Diagnosis. Hindawi shock and Vibration.2020.

[87]. Shaojiang Dong, Kun He, Baoping Tang. The fault diagnosis method of rolling bearing under variable working conditions based on deep transfer learning. Journal of the Brazilian Society of Mechanical Sciences and Engineering. 2020

[88]. Haedong Jeong, Seungtae Park, Sunhee Woo, and Seungchul Lee. Rotating Machinery Diagnostics using Deep Learning on Orbit Plot Images. Procedia Manufacturing. 2016; 5:1107-1118.

[89]. Chih-Hao Chena, Rong-Juin Shyua and Chih-Kao Mab. A new fault diagnosis method of rotating machinery. Shock and Vibration. 2008; 15:585–598

[90]. Chuan Li, René-Vinicio Sánchez, Grover Zurita, Mariela Cerrada and Diego Cabrera. Fault Diagnosis for Rotating Machinery Using Vibration Measurement Deep Statistical Feature Learning. Sensors. 2016; 16:1-19.

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