CHAPTER 1

Introduction

The catastrophic failure of engineering systems due to faults occurring on different vibrating components is still a great challenge. Health monitoring of such structures can be done as a preventive method to avoid huge financial losses by understanding the hidden messages in a different type of signals emitted by them.

1.1 Motivation and Problem Statement

Human safety is a massive motivation if someone thinks about aeroplane crashes, house or bridge collapses due to earthquake, or impacts where many lives have been lost. The associated financial losses due to replacement and uniaxiality are also very significant. It has been observed that:

(1) In 1987, LOT Polish Airlines Flight 5055 Il-62M crashed because of failed bearings in one engine, killing all 183 people on the plane [104].

(2) Bearing is the main source of system failure. Motor bearing faults account for more than 40 percent of the induction motor's failure [284].

(3) The Bearing is cheap, but the failure of bearing is costly. A $ 5,000 wind turbine bearing replacement can easily turn into a $250,000 project, not to mention the cost of downtime [161].

(4) The Gearbox bearing failure is the top contributor of the wind turbines downtime [29],

Figure 1.1: In 1987, LOT Polish Airlines Flight 5055 Il-62M crashed because of failed bearings in one engine, killing all 183 people on the plane

Figure 1.2: Offshore wind turbines

[197]. The second and probably dominant motivation (not surprisingly) that drives forward the research in this field is the need of private or public industries. A significant number of structures undergo routine inspections and maintenance to ensure the structural stability of the system. Detection of damage at an early stage could entail big economic savings. The costs of

these routine inspections could be significantly reduced if these inspections are shown to be unnecessary when a structure continues to be healthy, and this could automatically be indicated by implementing a SHM system. SHM could offer robust and online monitoring and necessary maintenance or repairs could be addressed based on this technology. Imagine the downtime cost of an offshore wind turbine or an offshore oil platform when a structure may undergo routine maintenance or emergency component replacement, which, in turn, would be an economic and environmental disaster.

Furthermore, nowadays, companies both in energy (an example is nuclear power plants) and the aerospace industry are keen on extending the initial lifetime of these structures. Of course, with aging comes "life fatigue" and economic issues are arising regarding the stability of these structures. SHM could offer a vital tool in inspecting continuously the systems for potential failures. Last but not the least is the defence industries. The military market is keen on developing SHM technology to detect damage and predict the operational lifetime of the structure during combat missions. SHM is the technology that will potentially allow the time-based inspection and maintenance to move into condition-based maintenance approaches. The basic philosophy behind the condition-based maintenance is that a holistic and robust sensor network will monitor the system and via smart measurement, processing will arise an alert to the operator in case of system abnormalities.

The diagnostic methods to identify these faults can be based on:

Temperature measurements,

Infrared recognition,

Radio frequency (RF) emissions monitoring,

Vibration monitoring,

Acoustic noise measurements,

Motor current signature analysis (MCSA),

Artificial intelligence and Machine Learning based techniques

Structural Health Monitoring (SHM) refers to the process of detection, diagnosis, and prognosis of damage in engineering structures and to evaluate the condition of existing structures for assurance of the safety of users. SHM research spreads to the areas of civil, mechanical, and aerospace engineering. During the early stages of development of SHM, the primary method of monitoring of structures was a visual inspection. As part of solid engineering interest, it probably started around the decade of the 1970s [49].

Structural Health Monitoring (SHM) has three components; Detection, Diagnosis, and Prognosis. Detection is a warning issued by the SHM technique that some abnormality has occurred. Diagnosis notifies the type of fault, its location, and its extent. Diagnosis has two categories, passive and active diagnosis. Prognosis is for computation of the severity of the crack in terms of fracture mechanics parameters, and its Remaining Useful Life (RUL). Hence the objective of structural health monitoring is a four-fold task, i.e., determination of damage existence, determination of damages geometric location, quantification of damage severity, and prediction of remaining useful life of the structure.

This chapter aims to provide a general introduction to the field of SHM and the advantages of a robust SHM system.

1.2 The Fundamental Axioms of Structural Health Monitoring

As stated by Farrar and Worden (2012), the fundamental axioms of structural health monitoring are basic guiding principles to design any SHM tool/procedure. They are as follows:

Axiom I: All materials have inherent flaws or defects.

Axiom II: The assessment of damage requires a comparison between two system states.

Axiom III: Identifying the existence and location of damage can be done in an unsupervised learning mode, but identifying the type of damage present and the damage severity can generally only be done in a supervised learning mode.

Axiom IV a: Sensors cannot measure the damage. Feature extraction through signal processing and statistical classification is necessary to convert sensor data into damage information.

Axiom IV b: Without intelligent feature extraction, the more sensitive a measurement is to damage, the more sensitive it is to changing operational and environmental conditions.

Axiom V: The length- and time-scales associated with damage initiation and evolution dictate the required properties of the SHM sensing system.

Axiom VI: There is a trade-off between the sensitivity to damage of an algorithm and its noise rejection capability.

Axiom VII: The size of damage that can be detected from changes in system dynamics is inversely proportional to the frequency range of excitation.

1.3 The Definition of Defect, Damage and Fault

As stated by Farrar and Worden (2012), A *defect* is inherent in the material, and statistically, all materials will contain a known number of defects. This means that the structure will operate at its optimum if the constituent materials contain defects.

Damage can be defined as changes that are introduced into a system, either intentionally or unintentionally, that will affect the current or future performance of the system. This system could be a structure or a biological organism. *Damage* is when the structure is no longer operating in its ideal condition, but it can still function satisfactorily, but in a sub-optimal manner.

In the context of SHM, damage can be defined as intentional or unintentional changes to the material and geometry of the structure [61]. The changes can be found at the macroscopic level as well as the microscopic level. Macroscopic change refers to the cracks due to fatigue, impact, and corrosion. The microscope changes are concerned with material matrix abnormalities. A few decades earlier, the microscopic material faults were difficult to detect in much advance. Now, with a lot of development in material technology, it is quite possible to find failures due to a material fault.

A *fault* is when the structure can no longer operate satisfactorily. If one defines the quality of a structure or system as its fitness for purpose or its ability to meet customer or user requirements, it suffices to define a fault as a change in the system that produces an unacceptable reduction in quality.

1.4 The Significance of SHM

The significance of SHM lies in the fact that many incidents occur where a building or bridge collapses, or, an aeroplane crashes, resulting in the massive loss of human life. Another factor which motivates for SHM in the industries is the economic aspect. A significant number of structures undergo routine inspections and maintenance to ensure the structural stability of the system. If the damage is detected at an early stage, a lot of money can be saved, which enhances profitability. By applying intelligent SHM techniques, unnecessary routine maintenance can be avoided and thereby reduce the downtime cost of the product. A robust online SHM system can avoid the failure of a power plant turbine due to the sudden requirement of replacement of bearings. We suffer a huge downtime cost in such cases. Furthermore, the power generation companies and aerospace industries focus a lot on increasing the lifetime of equipment/machinery. The issue of reliability and availability of these structures becomes critical with aging.

SHM could offer a vital tool in inspecting continuously the systems for potential failures. Last but not the the least is the defence industry. The defence industry, which has a worldwide market for arms and ammunition, has significant SHM application. SHM is the technology that will potentially allow the time-based inspection and maintenance to move into condition-based maintenance approaches. The basic philosophy behind the condition-based maintenance is that a holistic and robust sensor network will monitor the system and via smart measurement, processing will arise an alert to the operator in case of system abnormalities. The critical steps for a holistic SHM investigation are well described in Rytter's hierarchy (1993) and Worden and Dulieu-Barton (2009) with several small suggestions and additions to this hierarchy but without changing the nature of Rytters description. These levels can be summarised as follows:

Level One: Existence of damage to the system (Detection).

Level Two: Identification of where damage has appeared in the system (Localisation).

Level Three: Which is the specific kind of damage (Type).

Level Four: Investigation of damage severity (Quantification).

Level Five: Prediction of the remaining useful life in the system (Prognosis).

1.4.1 SHM for Rotating Machinery

SHM, mainly referring to damage detection in rotating machinery [300], is sometimes termed as Condition Monitoring (CM). CM has demonstrated considerable success and is considered a mature technology compared to SHM in general. Several factors can be considered as the key elements for this more established approach. The basic ones are, that rotating machinery gives specific dynamic response for specific fault classes, and as a result, failure detection and identification are more precisely readable [213]. This is also aided by the fact that machinery operates in a controlled environment, and their size is relatively small compared to the size of the structures SHM targets (bridges or skyscrapers). Non-Destructive Evaluation (NDE) is another method for this purpose.

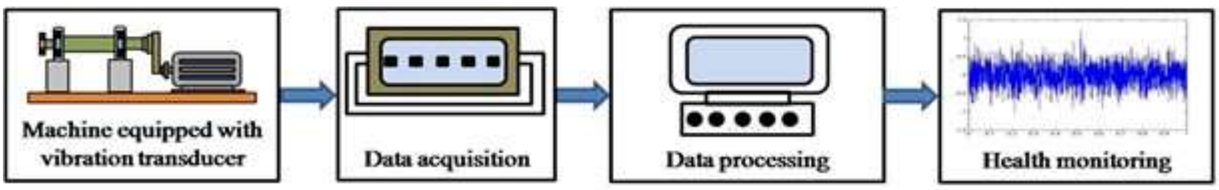

Figure 1.3: A rotary machine monitored using vibration signals analysis

NDE has been used successfully used in many practical engineering applications [300],[239]. In contrast with SHM that operates continuously and online, NDE is commonly carried out offline. NDE procedures exploit acoustic emissions, X-rays, and microscopy for evaluation. NDE tools are applied to the small parts of big structures where the damage is supposed to exist. A simple flow chart for vibration analysis of rotating machinery is shown in Figure 1.3.

1.5 Pattern Recognition

In the machine learning community, sensors cannot directly measure the types of faults on the rotating machinery. That's why features are extracted from the raw material and further processed by Signal Processing tools. The aim of feature extraction is to reduce the dimensionality of raw data measured through sensors. In machine learning, this drawback is referred to as the curse of dimensionality. After the extraction of these features, a suitable algorithm is devised which can distinguish the different faults existing on the rotating machinery/structures. The classification of damage is a pattern recognition problem and is the part of the machine learning family.

For the purpose of classification of faults, Machine Learning is applied in two ways, namely supervised learning and unsupervised learning. In terms of the SHM field, supervised learning means, any procedure of classification of a feature, which is trained with measurements labelled by all conditions of interest. At the first level, this is translated simply into the separation between the damaged and undamaged condition of the structure. At higher levels, via supervised learning, identification of different types of damage or localization of damage can be obtained. In several damage detection approaches, it is never possible, or it is very difficult to obtain true measurements for all possible damage classes, especially in high-value or complex structures such as composite systems. Furthermore, data that is collected during a damaged state of the structure is very rare. The premise of novelty detection techniques is to seek the answer to a simple question; given a newly presented measurement from the structure, does one believe it to have come from the structure in its undamaged state? Through the possession of data assured to be from the normal, undamaged condition of the structure, one can generate a statistical representation of the training data. After this training procedure, any generated data from the system can be tested and compared to the undamaged model; any suspicious deviation from normality can be said to be indicative of damage. The advantage of novelty detection is clear; any abnormality defines a new situation characterized by a truly new event for the structure.

1.6 Machine Learning (ML)

Machine learning (ML) is the study of algorithms and statistical models that computer systems use, relying on patterns and inference. Machine learning algorithms build a mathematical model based on sample data, known as" training data," to make predictions or decisions. It is seen as a subset of artificial intelligence.

Machine learning is divided into three groups: Supervised, unsupervised and semi-supervised. Supervised machine learning is a type of machine learning where the sample in the data set is labelled. The classifier uses in training set to learn a set of parameters and tries to classify the testing set successfully using the learned parameters. Unsupervised machine learning methods try to find hidden structures in unlabelled data. Semi-supervised machine learning uses both labelled and unlabelled data. Commonly conducted practice in semi-supervised machine learning is how to use a small amount of labelled data and a large amount of unlabelled data for training, and a large amount of labelled and a small amount of unlabelled data for testing. All supervised machine learning methods used in training data to train the hypothesis function for future prediction $h(\theta)$. Training data is defined as such:

$$S= \{(X_i , Y_i) \mid \forall\ i \in \{1,.....,N\}\} \tag{1.1}$$

Where S is the training data set, X_i extracted features, Y_i is the classification of i^{th} member of training data and N is the number of subjects for the training of hypothesis function h (θ),

where (θ) = $\{[\theta]_i \mid \forall i \in \{1, \ldots\ldots.,.\ N\}\}$ for future predictions.

1.6.1 Support Vector Machine (SVM)

Support Vector Machine (SVM) is a non-probabilistic and binary linear classifier. The main idea behind SVM is the creation of distinct borders between partitions of given data to break multiple sections that could be used for classification purposes with the future data. Support Vector Machines are trained to produce a function that can predict the classification of future data. Support Vector Machines are vector machines are margin optimization models that can classify non-linear data using hyperplanes, rather than greedy output search systems. They use the data set S as to train the hypothesis function h (θ) for future prediction. However; the methodology is a bit different from other methods because SVMs' are used to classify data with already known clusters. Support Vector Machines initially determine the support vectors, which are the border elements of a cluster. Then a hyperplane equation is derived using these support vectors. The following equation is solved for hyperplane parameters:

$$X_S * W - b = \{ Y_S \mid \forall\ X, W, Y \} \tag{1.1}$$

Where W is the set of normal vectors that are defined as

W = { W_i(x, y) | ∀ ∈ {1, ……, t}}, X_s is s^{th} support vector, b is constant in the hyperplane equation, Y is the solution set of the equation.

1.6.2 Neural Networks (NN)

Neural networks are a set of algorithms, modelled loosely after the human brain, that is designed to recognize patterns. They interpret sensory data through a kind of machine perception by labelling or clustering raw input. The patterns they recognize are numerical, contained in vectors, into which all real-world data, be it images, sound, text, or time series, must be translated.

1.6.3 Classification by Neural Networks

All classification tasks depend upon labelled datasets; that is, humans must transfer their knowledge to the dataset in order, for a neural network to learn the correlation between labels and data. This is known as supervised learning.

1.6.4 Clustering

Clustering or grouping is the detection of similarities. Deep learning does not require labels to detect similarities. Learning without labels is called unsupervised learning. Unlabelled data is the majority of data in the world. One law of machine learning is: the more data an algorithm can train on, the more accurate it will be. Therefore, unsupervised learning has the potential to produce highly accurate models.

1.6.5 Neural Network Elements

Neural Network is composed of several layers. The layers are made of nodes. A node is just a place where computation happens, loosely patterned on a neuron in the human brain. A node combines input from the data with a set of coefficients, or weights. These input-weight products are summed, and then the sum is passed through nodes so-called activation function. The activation function determines the output a node will generate, based upon its input. In Deep-learning, the activation function is set at the layer level and applies to all neurons in that layer. If the signals pass through, the neurons, they are said to be "activated." A node layer is a row of those neuron-like switches that turn on or off as the input is fed through the net.

A neural network can be thought of as a directed graph composed of nodes that represent the processing elements (which are like neurons), and arcs that represent the connections of the nodes (like synaptic connections) and directionally on the arcs, that represent the flow of information, as illustrated in the Figure 1.4.

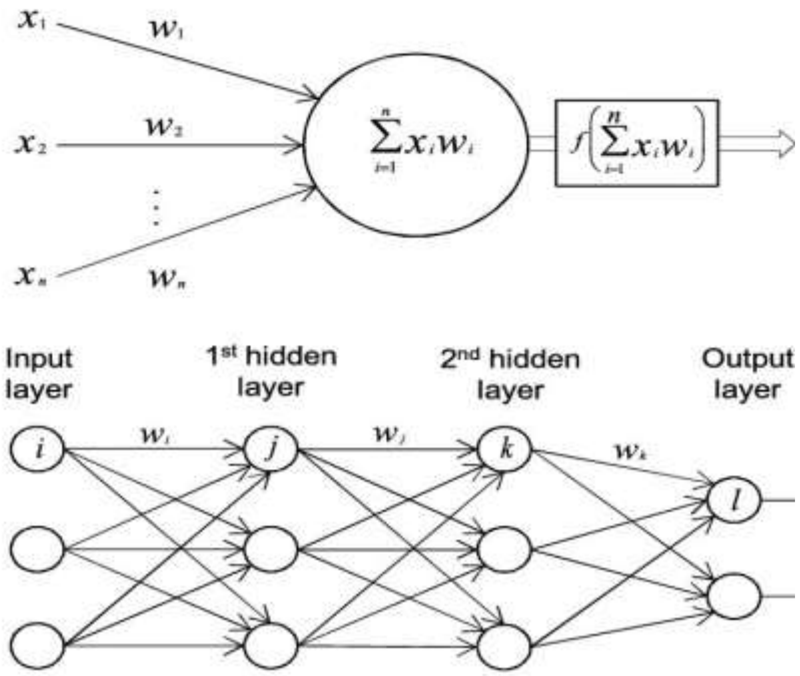

Figure 1.4: Neural network model

The signal is propagated through network and output signal, which can be put to a threshold to yield and output for affected (case) or unaffected(control).

Let's define

$W_{ji}^{(k)}$ = Weight of the connection between node j in layer k with node i in layer k+1

$H_j^{(k)}$ = The output value of node J in layer k

NN can be expressed as a weighted linear combination of inputs. For example, the output from input nodes in the first hidden layer can be written as:

$$H_j^1 = \sigma\left(\sum_i w_{ji}^{(0)} X_i\right) \qquad (1.2)$$

Where σ is in nonlinear activation function usually chosen as to be the sigmoid $1/\ (1+\ e^{-k}\ )$ and w_{ji}^0 are the weights for the connections between input nodes X_i and node H_j^1 in hidden layer 1. The output for the nodes in subsequently hidden layers can be written as a recurrence relation between the previously hidden layer nodes

$$H_j^{(k)} = \sigma\left(\sum_i w_{ji}^{(k-1)} H_i^{(k-1)}\right) \qquad (1.3)$$

and the target output can be modelled as a linear combination of hidden layers as;

$$\text{Output} = \sum_{jk} H_j^{(k)} \qquad (1.4)$$

The input pattern vector that is propagated through the network can consist of continuous or discrete values. This is also true for the output signal. Designing the network architecture must take into account the representation of the input pattern vector and its interaction with the network while propagating information through the network. Thus, the data representation must be suitable to detect the features of the input pattern vector so that it produces the correct output signal. A large field of neural network design has been devoted to the question of proper data representation.

Since learning and memory are thought to be associated with the strength of the synapse setting the strength of neural network connections is the mechanism that allows the network to learn the connection strength together with their input to the activity level, which is then used as input for the next layer of the network. Since learning is associated with synaptic weights, the backpropagation algorithm minimizes the error by changing the weights following each pass to the network. Hill -climbing algorithm make small changes to the weights until it reaches a value to which any change makes the error in weight higher, indicating that error has been minimized

1.6.6 Deep-Learning Neural Networks

Earlier versions of neural networks such as the first perceptrons were shallow, composed of one input and one output layer, and at most one hidden layer in between. More than three layers (including input and output) qualifies as "deep" learning. In deep-learning networks, each layer of nodes trains on a distinct set of features based on the previous layers output. The further one advances into the neural net; the more complex the features the nodes can recognize since they aggregate and recombine features from the previous layer.

This is known as a feature hierarchy, and it is a hierarchy of increasing complexity and abstraction. It makes deep-learning networks capable of handling very large, high-dimensional data sets with billions of parameters that pass through nonlinear functions. Deep-learning networks perform automatic feature extraction without human intervention, unlike most traditional machine-learning algorithms. When training on unlabelled data, each node layer in a deep network learns features automatically by repeatedly trying to reconstruct the input from which it draws its samples, attempting to minimize the difference between the networks guesses and the probability distribution of the input data itself. Restricted Boltzmann Machine (RBM), for examples, creates so-called reconstructions in this manner.

1.7 Data-Driven Methods for Fault Diagnosis

A quantitative knowledge-based or **Data-Driven Methods** is to essentially formulate the diagnostic problem solving as a pattern recognition problem. Quantitative information (or features) can be extracted by using either statistical or non-statistical methods. Therefore, the quantitative knowledge-based fault diagnosis can be roughly classified into statistical analysis-based fault diagnosis and non-statistical-analysis-based fault diagnosis.

1.7.1 Statistical-Analysis-Based Data-Driven Fault Diagnosis

Under a statistical framework, the quantitative knowledge-based fault diagnosis methods are mainly composed of Principal Component Analysis (PCA), Partial Least Squares (PLS), Independent Component Analysis (ICA), statistical pattern classifiers, and the most recently developed Support Vector Machine (SVM). It is evident that the methods above require a large amount of training data to capture the key characteristics of the process by using statistical analysis.

PCA is the most popular statistically-based monitoring technique, which is utilized to find factors with a much lower dimension than the original data set so that the major trends in the original data set can be properly described. PCA-based fault diagnosis methods have been investigated in depth and have successful applications in complex industrial systems. For instance, a nonlinear extension of the PCA was developed in [289] for diagnosing diesel engines. For a time-varying industrial process (e.g., a non-isothermal continuous stirred tank reactor system), a recursive PCA fault diagnosis method was presented in [55]. Owing to the ability of denoising original signals and improving the signal-to-noise ratio, probabilistic PCA-based fault diagnosis techniques were employed to monitor a rolling bearing with an outer race fault [109]. By integrating y-indexes, residual errors, and faulty sensor identification indexes with the PCA, two readily implementable and computationally efficient fault diagnosis approaches were addressed for gas turbine engines [326].

PLS is one of the dominant data-driven tools for complex industrial processes. The recent development of PLS-based monitoring and fault diagnosis can be found in [48],[276],[329]. Specifically, in [48], a data-driven scheme of key performance indicator prediction and diagnosis was proposed for both static and dynamic processes, which offered an alternative solution to the PLS method with simplified computation procedures. By combining kernel-based PLS discriminant analysis techniques and pseudo sample projection, a fault diagnosis method was presented in [276], providing efficient fault discrimination and enabling a correct identification of the discriminant variables in complex nonlinear processes. An improved structure, i.e., Total Projection to Latent Structures (T-PLS), was addressed in [329] based on further decomposition for the obtained PLS structure. The proposed T-PLS-based method can well detect quality-relevant faults in industrial processes subjected to a variety of raw materials and changeable control conditions.

ICA plays an important role in real-time monitoring and diagnosis for practical industrial processes as it allows latent variables not to follow a Gaussian distribution. Recently, a kernel-ICA-based fault isolation method was proposed in [327] for non-Gaussian nonlinear processes. In [268], defect detection was investigated for solar modules by using ICA basis images detection. In [78], an ICA-based fault diagnosis technique was applied to the monitoring and diagnosis of a rolling-element bearing.

As a matter of fact, data-driven statistical tools such as the PCA, the PLS, and the ICA have been widely employed in feature extraction for microarray gene expression data, which facilitate and ease the understanding of biological processes [255]. On the other hand, a microarray enables expressions of tens of thousands of genes to be represented on a small array of coloured image dots, which may be utilized for a quick fault diagnosis for industrial processes. Motivated by the microarray visualization and utilizing simple statistical analysis of the measured values of different sensors and the graphical synopsis of the results of such analysis, a quick diagnosis of the key variables/steps that cause the fault in the final quality was achieved in [164].

The SVM is a relatively new machine learning technique relying on statistical learning theory, which is capable of achieving high generalization and of dealing with problems with low samples and high input features. The SVM is regarded as a potential technique for classifying all kinds of data sets. The initial attempts of applying the SVM to condition monitoring and fault diagnosis began in the late 1990s [259], [218]. The SVM-based machine condition monitoring and fault diagnosis methods dated to 2006 were well documented and reviewed in [294]. Recent results of the SVM-based fault diagnosis can be found in [319],[184],[220],[317]. Specifically, by integrating a kernel function and cross-validation, an SVM-based fault diagnosis approach was proposed in [319] for the Tennessee Eastman process, which showed a superior fault detection ability over the conventional PLS algorithm. With the aid of a genetic algorithm for parameter tuning, an SVM-based fault diagnosis method was presented in [31], which showed improving diagnosis performance. Utilizing *k*-nearest neighbour (KNN) algorithms to estimate plausible values to replace the missing values in the data set before SVM learning, an effective SVM based fault diagnosis technique was addressed in [220] for power transformers. In [317], a smart SVM-based functional fault diagnosis method that exploited multiple kernel functions and utilized incremental learning was proposed. By leveraging a linear combination of single kernels, the multi-kernel SVM method can achieve accurate faulty component classification based on errors observed, whereas incremental learning can allow the diagnosis system to quickly adapt to a new error observation, leading to even more accurate fault diagnosis.

1.7.2 Machine Learning-Based (Non-Statistical) Data-Driven Fault Diagnosis

Owing to its powerful ability in nonlinear approximation and adaptive learning, A Neutral Network (NN) has been the most well-established in -statistical-based data-driven fault diagnosis tool. In terms of topology, the NN can be classified into radial basis networks, recurrent dynamic networks, self-organizing maps, backpropagation networks, and extension networks. According to the learning strategy, NN-based fault diagnosis can be categorized into supervised-learning-based fault diagnosis and unsupervised-learning-based fault diagnosis. By using unsupervised learning, the knowledge base can be extracted from the historical data to emulate normal system behaviour, which is utilized to check whether the behaviour of the real-time process deviates from the normal system behaviour. By using supervised learning, the knowledge bases for normal systems and faulty conditions are all extracted, which are then utilized for real-time monitoring. Recent developments of the NN can be found in a variety of real-time applications, e.g., for combustion engines [237], nuclear processes [53], induction machines [267], [138].

Fuzzy logic (FL) is an approach of partitioning a feature space into fuzzy sets and utilizing fuzzy rules for reasoning, which essentially provide approximate human reasoning. FL has been successfully employed for fault diagnosis. For instance, in [333], FL was employed to represent a fuzzy knowledge base that was extracted from the current analysis and applied to detect misfiring in the switches in a Pulse Width modulation (PWM) source inverter induction motor drive. Recent developments have shown an interest to combine FL with other knowledge-based techniques such as expert systems or an NN for solving an engineering-oriented diagnosis issue or getting better diagnosis performance.

1.7.3 Joint Data-Driven Fault Diagnosis

In some practical applications, the statistic and non-statistic fault diagnosis data-driven methods are often utilized jointly. For instance, in [37], a Bayesian network and a recurrent NN were integrated to diagnose and isolate faults in induction motors, where the NN was

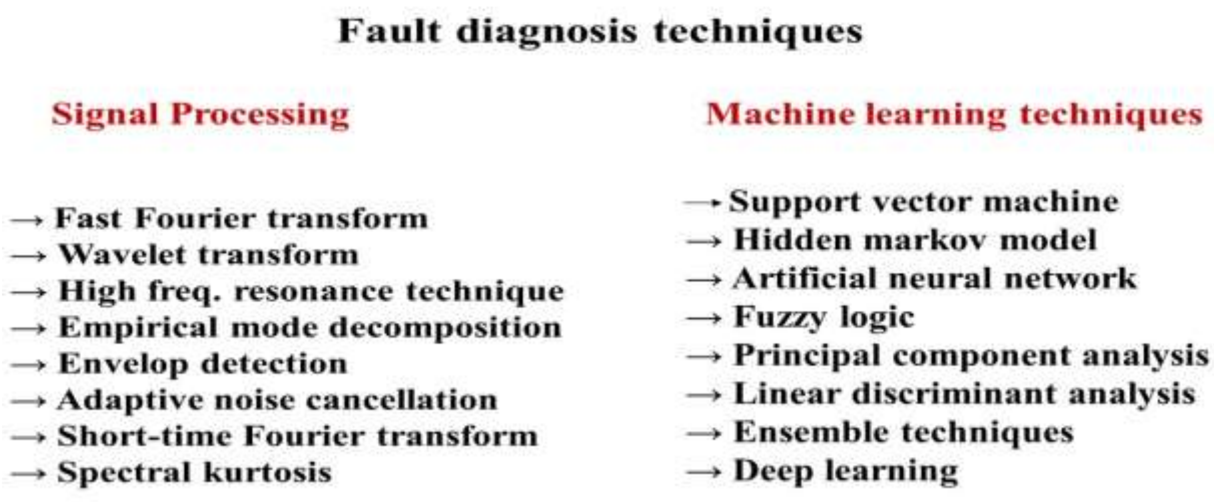

Figure 1.5: Fault diagnosis techniques

used to train the data from the system under normal operating conditions and known faulty conditions, whereas the stochastic Bayesian network was employed to produce random residuals.

A supervised method and an unsupervised method are two major training and search manners in data-driven fault diagnosis. For the unsupervised approach, the data recorded from the normal operation of the practical system are trained to form a knowledge base, which is then utilized to monitor the deviations against a real-time process. In the supervised method, a classifier is trained on the annotated historical data recorded from both normal and faulty conditions, which is then employed for fault prediction. Supervised and unsupervised methods have their own advantages and disadvantages. To enhance their advantages, a natural idea is to combine the supervised method and the unsupervised method for fault diagnosis. Joint methods are again classified as signal processing and machine learning type methods as shown in Figure 1.5.

1.8 Contributions of the Thesis Work

This thesis provides several significant contributions to the analysis and modelling of machine learning-based data-driven methods which lay the foundations for the solution of structural health monitoring problems. We presented the application of machine learning methods for early prediction of the failures of self- priming centrifugal pumps with the help of methods like Support Vector Classification (SVC), Multinomial Logistic Regression (MLR), Artificial Neural Networks (ANN) and especially, Convolution Neural Networks (CNN). The thesis presented a smart enhancement technique which shows its effect in providing better classification results in all machine learning algorithms.

Our main focus has been how to apply deep learning methods for the structural health monitoring of mechanical systems. We succeeded in our task in identifying the early failures of bearings due to the cracks developed on small rollers.

In this research work, we have addressed the problem of estimation of Remaining Useful Life successfully, as an important part of prognostics. A new method based on stacked gradient boosted trees has been explored and implemented successfully.

The accuracy, reliability, and computational cost are crucial issues in any efficient method. The machine learning methods require the least time and least number of iterations to complete the process of detection of the fault.

1.9 Organization of Thesis

The research work documented in this thesis comprises six chapters. The details of each chapter are as follows:

Chapter 1 consists of a general introduction, major bearing faults, and their root causes. The reasons for and procedure of using vibration-based health monitoring techniques are discussed. Various possible sources of nonlinear vibrations in rolling element bearings are summarized. This chapter also includes the objective and organization of this thesis.

Chapter 2 comprises the survey of published literature. It includes a discussion on the use of various signal processing and machine learning techniques for health monitoring. A comprehensive evaluation of fault diagnosis and prognosis methods have been discussed.

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Chapter 3 This chapter deals with the development of an enhanced data technique, which is very useful for the smaller size of available data. It is proposed to increase the size of data to multiple times until a good classification accuracy is acquired. The method shows that the neural networks perform very efficiently when such type of enhancement is done. It has been elaborated for evaluating the classification of faults of self-priming centrifugal pumps. The classification of pump faults is achieved to almost 100 percent by deep neural networks. The precision-recall curves have been used to evaluate the performance of five machine learning models.

Chapter 4 presents a new compound fault diagnosis method of rolling bearing. We have proposed a method based on the use of Combined Mode Functions (CMF) for selecting the Intrinsic Mode Functions (IMFs) with EEMD technique, sandwiched with, Convolution Neural Networks (CNN), which are deep neural networks, used as fault classifiers. This composite CNN-CMF-EEMD method overcomes the deficiencies of other approaches, such as the inability to learn the complex non-linear relationships in fault diagnosis and, to detect the fine compound faults occurring on small balls of the bearing. The difficult compound faults are separated effectively by executing CNN-CMF-EEMD method. It makes the fault features more easily extracted and more clearly identified.

In **Chapter 5**, the remaining useful life of an engine is assessed. This chapter presents a novel machine learning model for this task, which includes a smart ensemble of Gradient Boosted Trees (GBT) and feed-forward neural networks. It incorporates discussions on the poor performance of Multi-Layer Perceptron (MLP) and the need of ensemble models. Initial stages of data exploration and pre-processing are also comprehensively documented. Experiments are performed on the four run-to-failure datasets by Commercial Modular Aero-Propulsion System Simulation (C-MAPSS). It concludes by presenting evaluations of multiple prediction models like MLP, Support Vector Regression (SVR), Convolution Neural Networks (CNN) and Gradient Boosted Trees (GBT).

Finally, **Chapter 6** summarizes the important conclusions drawn from this research work.

The few important suggestions for future work are also presented in this chapter.

1.10 Conclusions

The general motivation behind the SHM was presented in this introductory chapter, including the basic elements of this research to be applied in practice. Machine learning based SHM is a field of research with increased interest due to the major advantage of operating continuously and globally. The challenges are the development of a robust and online SHM system that is capable of detecting early critical fault types during the structure operation independently, in changing environmental and operational conditions. This thesis undertakes a serious attempt to apply SHM technology in a solid and fast manner by investigating how to simplify complex machine learning approaches into a simpler form and to determine a robust way to resolve the often-encountered problem of external operational factors.