



## Survey paper

## Multi-fault diagnosis of Industrial Rotating Machines using Data-driven approach : A review of two decades of research



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## ABSTRACT

Industry 4.0 is an era of smart manufacturing. Manufacturing is impossible without the use of machinery. The majority of these machines comprise rotating components and are called rotating machines. The engineers' top priority is to maintain these critical machines to reduce the unplanned shutdown and increase the useful life of machinery. Predictive maintenance is the current trend of smart maintenance, followed by most maintenance engineers. The challenging task in predictive maintenance is to diagnose the type of fault. With Artificial Intelligence (AI) advancement, a data-driven approach for predictive maintenance is taking a new flight towards smart manufacturing. Several researchers have published work related to fault diagnosis in rotating machines, mainly exploring a single type of fault. However, a consolidated review of literature that focuses more on the "multi-fault diagnosis" aspect of rotating machines is lacking. There is a need for a study that would systematically cover all the aspects right from sensor selection, data acquisition, feature extraction, multi-sensor data fusion to the systematic review of AI techniques employed in multiple fault diagnosis. In this regard, this paper attempts to achieve the same by implementing a systematic literature review on a Data-driven approach for multi-fault diagnosis of Industrial Rotating Machines using the "Preferred Reporting Items for Systematic Reviews and Meta-Analysis" (PRISMA) method. The PRISMA method is a collection of guidelines for the composition and structure of systematic reviews and other meta-analyses. This paper identifies the foundational work done in the field and gives a comparative study of different aspects related to multi-fault diagnosis of industrial rotating machines. The paper also identifies the major challenges, research gap. It gives solutions using recent advancements in AI in implementing multi-fault diagnosis, giving a strong base for future research in this field.

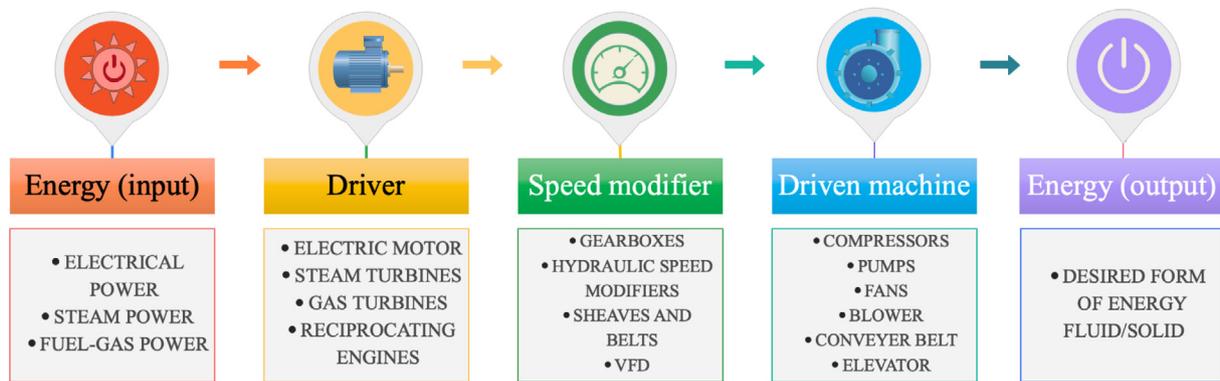
## 1. Introduction

Industries are the basis of the nation's economy. With the recent advancement in technology, especially in Artificial Intelligence (AI), these industries have achieved new heights by transforming into smart factories, marking an era of the fourth industrial revolution. Smart factories employ smart manufacturing, and the basic building block of any manufacturing process industry is the machines. Most of the machines in the industries comprise rotating components and are called rotating machines (Mohanty, 2014). More precisely, the rotating machines facilitate the transfer of energy to fluids and solids or vice versa. The rotating machine consists of the rotating part, which we call a rotor, and the static part called a stator (Bigret, 2001). In the process industry, a train of rotating machines is used to transport solids,

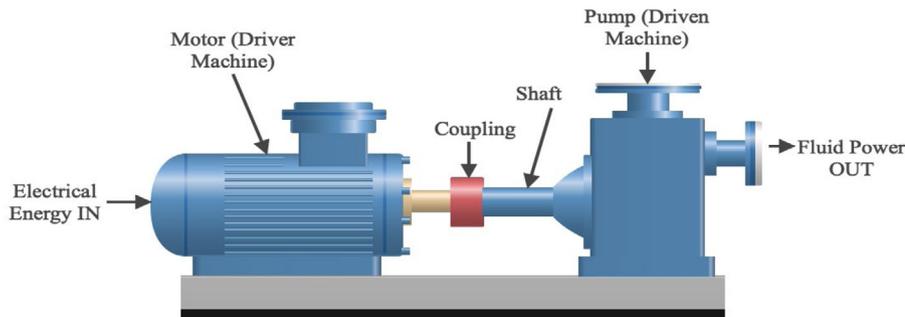
liquids, and gases (Operations and Uptime, 2006). Process machinery comprises a group of sub-elements (of rotating machines) that combine to convert one form of energy until converted into the desired usable form of energy. There are different sub-elements, including the driver machines, the driven machines, the speed modifiers, the shaft, and the coupling. The driver machines take electrical, steam, or fluid energy and convert it into rotary power that can be used to drive a process machine. Electric motors, turbines, reciprocating engines (usage is very less) are examples of driver machines. Driven process machine transports a given process fluid or solid, at a given flow and pressure, to specific points in a process. Pumps, fans, compressors, conveyor belts, etc., are widely used driven machines. The speed of the driver output shaft may be increased or decreased by a speed modifier,

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### a. Flow Diagram of Process Rotating Machinery



### b. An Electric Motor coupled to a Centrifugal Pump.

Fig. 1. Representation of rotating machines.

depending on the requirement of the process machine being driven. Gearboxes, sheaves, and belts are examples of rotating machines that work as speed modifiers. However, Variable Frequency Drive (VFD) is electronic equipment used as a speed modifier. A shaft is a rotating machine element used to transmit energy from the driver to driven machinery. The shaft on the driver side is connected to the driven side using coupling. Fig. 1 shows the representation of rotating machines with Fig. 1a (Operations and Uptime, 2006) giving the flow of the energy is transfer in the process of rotating machines, and Fig. 1b gives an example of the train of rotating machines comprising an electric motor coupled to a pump.

From the above discussion, it is evident that any manufacturing process is incomplete without rotating machines. Therefore, it is essential to keep such machines in healthy operating conditions by deploying proper maintenance strategies (Gawde and Borkar, 2018). Predictive maintenance is the current trend of smart maintenance, which most maintenance engineers follow. The challenging task in predictive maintenance is to diagnose the type of fault. With Artificial Intelligence (AI) advancement, a data-driven approach for predictive maintenance is taking a new flight towards smart manufacturing. The use of Big Data for multiple fault diagnoses will be the prime focus of the study.

#### 1.1. Significance of the study

Rotating machines is the heart of any manufacturing process, and proper maintenance is the utmost priority of maintenance engineers. A proper maintenance strategy plays a vital role in the success of the manufacturing industry (Silvestri et al., 2020). Fig. 2 shows the P-F Curve (Nowlan and Heap, 1978), which depicts how equipment fails and how early identification of a failure allows time to plan and arrange the replacement or restoration of a failing item without causing a manufacturing slowdown. P denotes Potential failure (based

on historical data), and F denotes Functional failure (actual failure) in a P-F Curve (Du Toit, 2014). The main aim of any maintenance engineer is to minimize probability of failure using various maintenance strategies (Biggio and Kastanis, 2020). The figure also depicts the relation between the condition of the equipment and the cost to repair concerning the time taken to implement appropriate maintenance action. With the correct type of maintenance strategy, one can detect early failure mode.

It is very clear from Fig. 2 that it is crucial to have an early fault diagnosis to save the industrial economy. Digital transformation in Industry 4.0 has made it possible to collect a massive amount of data and effectively utilize it in fault diagnosis in Predictive Maintenance (PdM) (Çinar et al., 2020). It will reduce the unplanned downtime and increase the Remaining Useful Life (RUL) of the machinery (Sayyad et al., 2021a). Several researchers have published work related to fault diagnosis in rotating machines, mainly exploring a single type of fault. However, if we have to take complete advantage of Big Data, it is essential to not just focus on a single fault but to consider multiple faults that arise in the machinery (Luwei et al., 2018). The study is incomplete unless the AI models are generalized and detect maximum faults in real-time industrial environments with high prediction accuracy (Kumar et al., 2020). Also, most of the researchers have used single sensor data in fault diagnosis. A very few researchers have implemented multi-sensor data fusion, proving the drastic improvement in accuracy of diagnosis, taking into account the uncertainty of data (Jiang et al., 2017). Hence there is a need to consider this aspect of multi-sensor data fusion in future work. If a machine shows an unusual behavior or needs maintenance in the present scenario, a domain expert must diagnose the machinery's fault (Feng et al., 2021). It shows that the research in this field still has a long future as a full-fledged implementation of the fault-diagnosis aspect using AI is yet to be achieved. A consolidated literature review is needed to focus on the "multi-fault diagnosis"

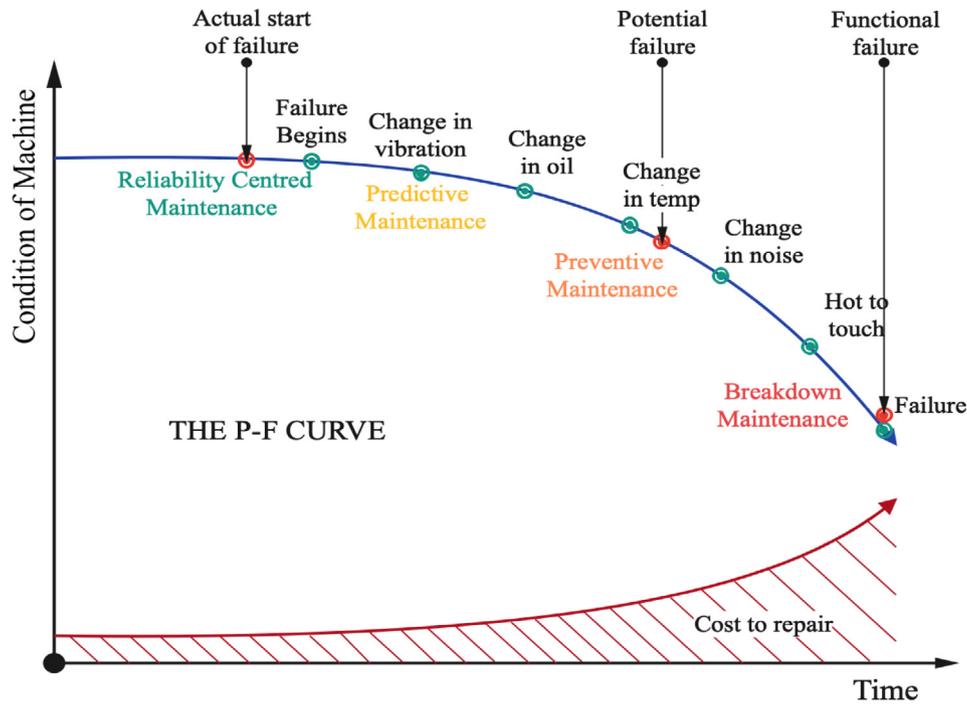


Fig. 2. The PF Curve depicting the significance of early fault diagnosis.

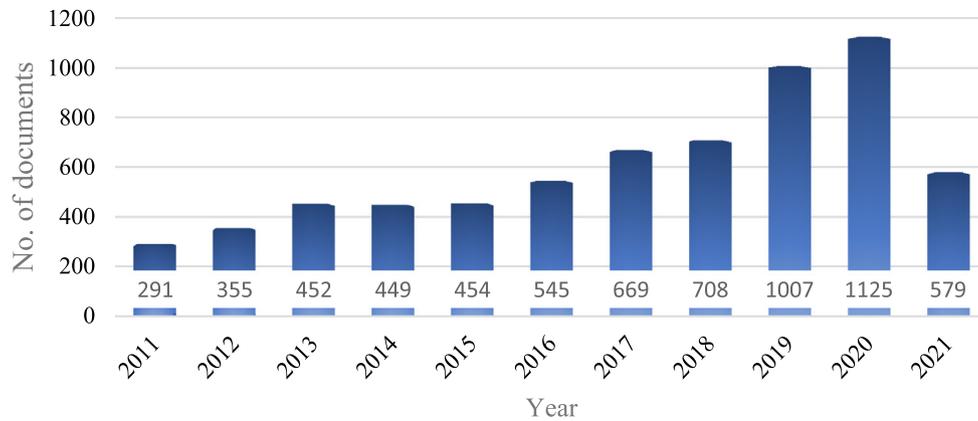


Fig. 3. Research trend in fault diagnosis of rotating machines over past ten years (2011–2021).

aspect of rotating machines to give a strong foundation for future research. There is a need for a study that would systematically cover all the aspects right from sensor selection, data acquisition, feature extraction, multi-sensor data fusion to the systematic review of AI techniques employed in multiple fault diagnosis. This paper is also a small attempt to review the aspects mentioned above from the past research using PRISMA guidelines for systematic review.

### 1.2. Motivation

Artificial intelligence is an ocean of tremendous opportunities. The application of AI techniques to solve real-life problems is the new trend of future research. Being closely associated with the problems faced by maintenance engineers, finding a solution to the same utilizing AI techniques is the primary motivation behind the study. Fault detection is pretty simple by setting alarm limits, while a correct fault diagnosis is equally complex. With the advancements in Big data analysis using AI models, it is possible to tackle this problem to a great extent. However, most research focuses on the single type of fault, a preliminary study

that needs further research. Also, the researchers have focussed on single sensor data, which again reduces the credibility of research as the health of machinery cannot be solely predicted based on a single sensor parameter. It is imperative to evaluate multiple parameters such as vibration, temperature, current, AE, etc., to get the complete condition of the machinery. To achieve this, multi-sensor data for fault diagnosis needs more exploration. The continuity in research lacks that would overcome the disadvantages of the previous work done. To explore the possible ways to solve the above problems, there is a need for an extensive literature survey. There is a need for study covering all aspects of multi-fault diagnosis, including big data acquisition, data processing, multi-sensor data fusion, and AI techniques that the researchers have already implemented. Such a study would give the gap in research and, in turn, motivate future research in the field. A very little encyclopedic research covered all the aforementioned aspects, which motivated the authors to explore more in this area. Fig. 3 shows a trend in research in the past ten years extracted from the Scopus database in the field of multi-fault diagnosis in rotating machines. It is clear from the figure that the research is developing in this field, begging researchers' significant attention every year.

### 1.3. Terms and terminology

Following are the terms frequently used in fault-diagnosis of Industrial rotating machines.

- **Industry 4.0:** Industry 4.0 (the fourth industrial revolution) is the current automation trend, a fusion of cyber-physical systems, the Internet of things, and cloud computing (Xu et al., 2018).
- **Predictive maintenance (PdM):** In predictive maintenance, engineers try to predict the failures of machines based on certain conditions prevailing in the machinery.
- **Big-Data Analysis:** Big data analytics uses advanced analytic techniques against vast, diverse datasets that include structured, semi-structured, and unstructured data from different sources and in different sizes, from terabytes to zettabytes.
- **Artificial Intelligence (AI):** A subset of big data where we simulate human intelligence on machines.
- **Data-driven approach:** A data-driven approach gives decisions based on complex data analysis and interpretation rather than observation.
- **Multi-sensor data fusion:** Sensor fusion is the process of combining sensory data or data derived from disparate sources such that the resulting information has less uncertainty than would be possible when these sources used individually.
- **Multi-fault diagnosis:** Diagnosing multiple faults in the machinery based on data processing and analysis.
- **Rotating machines:** Rotating machines are generally used in the oil and gas and process industries to describe mechanical components that use kinetic energy to move fluids, gases, and other process materials.
- **Maintenance strategy:** A maintenance strategy defines the rules for the sequence of planned maintenance work.

### 1.4. Evolution of maintenance strategies:

Rotating machinery is a machine with a rotating component that transfers energy to a fluid, solid, or vice versa. In the first section of the introduction, we have discussed the different types of rotating machines, including the driver and the driven rotating machines. We have also seen the significance of these machines for the manufacturing process. Hence, maintenance engineers' most important task is to keep them in a healthy working condition. Let us understand the various maintenance philosophies that have evolved over the years.

First on the list is the Run to failure or breakdown maintenance philosophy. The machine runs in its prevailing condition without any check-up, and maintenance will be carried out only after breakdown or failure. It is also often referred to as reactive or corrective maintenance (Mohanty, 2014). The temporary advantage is that it needs the least planning and hence no initial maintenance costs. On the other hand, it is expensive as the engineer waits until the end and acts based on the breakdown. Breakdown maintenance is an age-old technique but still followed in some machines, which are not so critical to the functioning of the plant. Demand for more complex machines due to increased rate of productivity made breakdown maintenance quite a lot expensive. At this point, another frequently used philosophy called preventive maintenance was introduced (Mohanty, 2014; Lee et al., 2015). Few commonly used synonyms for preventive maintenance are scheduled, planned, and sometimes calendar-based maintenance. As the name again suggests, the engineers try to prevent failure by periodic or planned maintenance activities. It is not wrong from a machinery health perspective, but it becomes costly considering the resource (time and money) consumption. Hence preventive maintenance is also avoided as it results in increased maintenance costs though ensuring excellent and stable machinery health. So, the engineers thought of changing this calendar-based maintenance to condition-based maintenance, which is called Condition Monitoring. Condition monitoring

(CM) is the technique of continuously monitoring a machine's condition parameter (vibration, temperature, etc.) to detect a substantial change that might indicate a growing defect.

In the present era of Industry 4.0, engineers came up with another logical approach: the philosophy of predictive maintenance (Okoh et al., 2017). Predictive Maintenance is based on Condition Monitoring, abnormality detection, and AI algorithms. It integrates predictive models that can estimate the remaining machine runtime left or diagnose the type of fault in machinery according to detected abnormalities. This approach uses a wide range of tools, such as statistical analyses and Machine Learning to predict the state of the equipment. The evolution of Maintenance strategies is as shown in Fig. 4 (Sayyad et al., 2021a; Çinar et al., 2020). Following are some applications of Predictive Maintenance:

**All types of Industrial plants:** Fans, pumps, electric motors, gearbox, etc.

**Pulp & Paper:** blowers, belts for conveyors, chippers, refiners, pressure screens, screw conveyors, agitators, nip monitors, felt rollers, etc.

**Iron & Steel:** Equipment for handling raw materials, conveyor belts, ship unloaders, galvanization facilities, cranes, rolling mills, pumps, fans, gearboxes, and other devices are also included.

**Automotive:** Presses and transfer presses, as well as wind tunnels, air handling systems, and pumps in paint factories, etc.

**Cement:** Crushers, gearboxes, conveyor belts, separators, fans, raw mills, ball mills, elevators, and blowers.

**Power generation plants:** gas turbines, steam turbines, water pumps, etc.

### 1.5. Multi-fault diagnosis in rotating machines

Manufacturing process machines, especially the rotating machines, work  $24 \times 7$ , resulting in mishandling or wear and tear due to prolonged use leading to different faults in them. The different components of rotating machines possess different types of faults. These faults are broadly classified at three levels: Component-level faults, System-level faults, and Interrelated faults. Component level faults include the faults related to bearing, shaft, pulley, etc. For example, Bearing is a component that is considered the heart of rotating machines that can have faults like inner race faults, outer race faults, rolling element faults, etc. Similarly, the shaft also is a component that can possess fault like misalignment, rotors in the rotating machines can have unbalance type of fault, and so on. Fig. 5 summarizes different types of component-level faults that can arise the rotating machinery. System-level faults include the faults of the overall system to be monitored. Interrelated faults include the additive faults (addition of different faults due to multiple components, e.g., Unbalance and Misalignment) and multiplicative faults (multiplication of different fault types in a single component, e.g., shaft bent and shaft crack). Additive faults can be better diagnosed as compared to multiplicative faults.

Many of the completed papers and models have diagnosed a single target fault. In today's era of big data, the single label system ignores the interrelationship of different fault types, making it difficult to accurately determine the location, type, and degree of mechanical failure (Zhao et al., 2020c). Sometimes one fault can give rise to other faults. A combination of different faults is also possible at the same time (Li and Liang, 2018). Considering this aspect, a proposed model for fault detection is valid or is deployable in real-life situations only if it can detect multiple faults (multi-faults) and not just one fault, which is seen in most of the research published. Multi-sensor data fusion (Jiang et al., 2017) also needs to be used to achieve multi-fault diagnosis with high accuracy. The key to accurate fault diagnosis is in identifying and separating the fault characteristics.

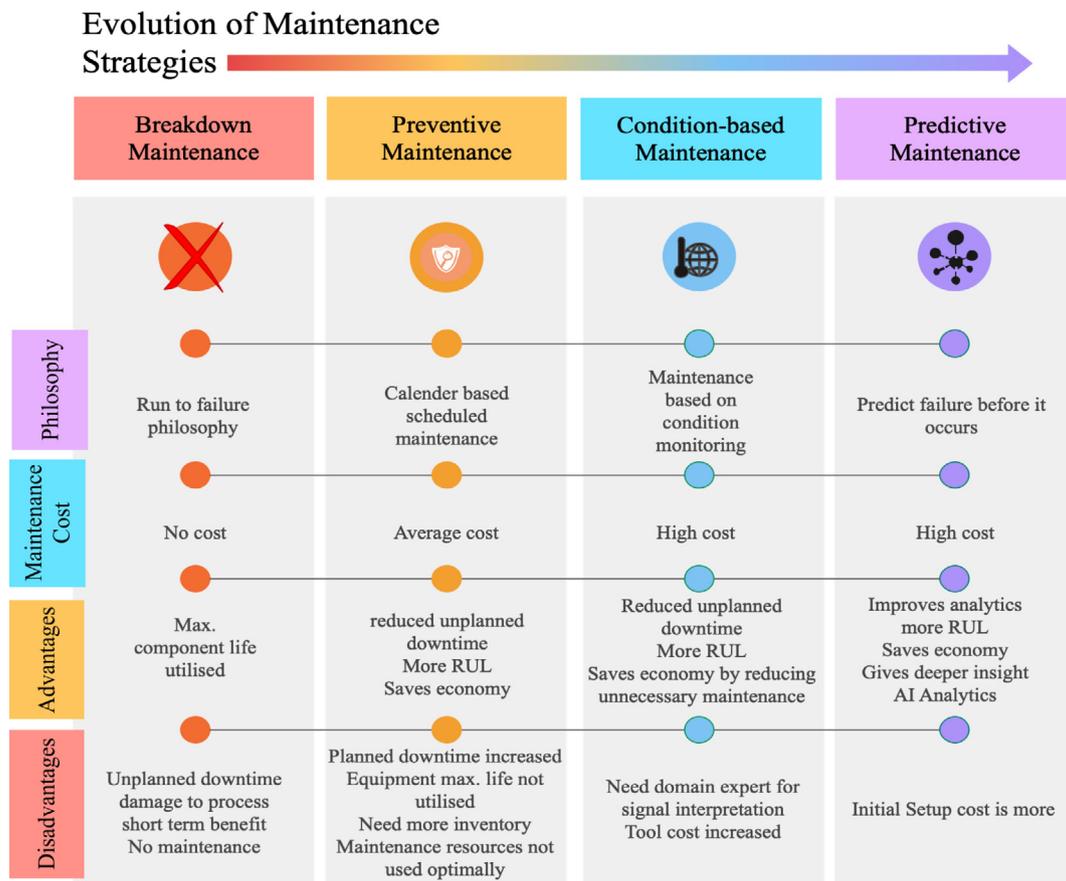


Fig. 4. Evolution of maintenance strategies.

#### 1.6. Prior research

The systematic literature review aims at answering the research questions by critically investigating the available research publications. However, as per the articles published related to multi-fault diagnosis of industrial rotating machines, very few papers have done a systematic literature review. Table 1 gives the comparative analysis of different review papers related to fault diagnosis in rotating machines. The table is so formulated that it compares the review papers published with different aspects. The questions are as stated below:

- i Are the review papers related to multi-fault diagnosis of rotating machines?
- ii Have the authors discussed sensor selection and multi-sensor data fusion?
- iii Is there a discussion on where to get data from or how to acquire data?
- iv How to extract features and do signal processing?
- v What are the different AI Approaches for diagnosis?
- vi What are the major challenges and future scope in this field?

A total of five papers have done a systematic literature review related to multi-fault diagnosis of rotating machines (Nath et al., 2021; Gundewar and Kane, 2021; Li et al., 2017; Jardine et al., 2006; Wang et al., 2017), out of which Nath et al. (2021), Li et al. (2017), Jardine et al. (2006) have discussed multi-sensor data fusion. It is also seen that almost all the papers (Nath et al., 2021; Gundewar and Kane, 2021; Wei et al., 2019; Li et al., 2017; Jardine et al., 2006; Montero Jimenez et al., 2020; Pech et al., 2021; Wang et al., 2017; Fahle et al., 2020; Li et al., 2019) have discussed in detail Artificial Intelligence techniques and models, the challenges in implementing accurate fault diagnosis, and what is the future scope based on the

survey. Most of the authors have also discussed the different approaches for fault detection: the statistical approach, the data-driven approach, and the hybrid approach. However, very little importance is given to the equally vital questions like what sensors(s) to use, how to acquire data, how to process the data, with what features to be extracted? All the empty fields in the table also need to be addressed as the proper selection of methods/technology is the key to accurate fault diagnosis. For instance, selecting multiple sensors instead of single sensors increases fault prediction accuracy (Jiang et al., 2017). Based on this prior research, the authors of this paper have tried to answer all the missed questions and remained unanswered from Table 1 to give a comprehensive review related to multi-fault diagnosis in Rotating machines.

#### 1.7. Technology focus and evolution time-line for Machine Health Monitoring

All technologies are created with a specific goal in mind. Search engines, for example, were built to sort through the vast amounts of data available on the internet. With each new upgrade, current technologies are combined to create something superior to what was before used. The list goes on and on. It is no surprise that many people have struggled to keep up with the rapid pace of technological advancement. To be fair, the scope of technology is so vast that condensing it all into a single section is impossible. Fig. 6 (Feldmann et al., 2018) shows the evolution in technology related to fault diagnosis in industrial rotating machines. The evolution is demonstrated concerning sensor technology, data and signal processing, condition monitoring & diagnosis, and maintenance strategies in the past years and the near future.

**Table 1**  
Comparative analysis of review papers related to fault/multi-fault diagnosis of industrial rotating machines.

References	Paper Features											Overview
	Multi fault diagnosis	Rotating machines	Sensor selection	Data source/ test setup	Data acquisition	Feature extraction / processing	Multi-sensor data fusion	AI Techniques	RUL	Challenges	Future Scope	
Nath et al. (2021)	●	●		●	●	●	●	●		●	●	Role of AI in rotor fault diagnosis
Gundewar and Kane(2021)	●	●						●		●	●	Fault diagnosis in Induction Motor
Wei et al. (2019)		●						●		●	●	Early fault diagnosis in rotating machines
Li et al. (2017)	●	●	●				●	●	●	●	●	Multidimensional prognostics for rotating machines
Jardine et al. (2006)	●	●				●	●	●	●	●	●	diagnostics and prognostics for CBM
Montero-Jimenez et al. (2020)		●						●	●	●	●	Multi-model approach for PDM
Pech et al. (2021)		●	●					●		●	●	PdM & intelligent sensors in smart factory
Wang et al. (2017)	●	●				●		●		●	●	multi-fault diagnosis of planetary gears
Fahle et al. (2020)		●						●		●	●	ML Methods for manufacturing process
Li et al. (2019)		●						●		●	●	Signal Processing methods for fault diagnosis

**Table 2**  
Research goals.

Sr. No.	Research question	Discussion
1	What are the different approaches employed to achieve multi-fault diagnosis under Predictive Maintenance (PdM) for rotating machines in Industry?	This section gives a comparative analysis of different PdM approaches discussing the advantages and disadvantages of each approach.
1	What are the available data sources for data-driven PdM? How to select the appropriate sensors for data collection?	Discussion related to online datasets and data collection on test setup is discussed along with Different sensors explanations.
2	What are the different data acquisition methods? What are the data validation techniques?	Critical points for data acquisition and validation techniques are discussed.
3	What are the different signal processing techniques?	Feature extraction and the types for signal processing are discussed.
4	What are the approaches to achieve Information fusion or multi-sensor data fusion?	Multi-sensor data fusion is discussed in detail.
5	How to implement AI models for multi-fault detection?	A data-driven and a hybrid approach are discussed for PdM.

**1.8. Research goal**

The presented Systematic literature review critically analyzes existing studies on the multi-fault diagnosis of industrial rotating machines using PRISMA guidelines. The literature review is achieved with the help of the critical questions formulated in Table 2. The table explains the research questions along with the discussion related to the question. The authors believe that the answers to the questions in the table will give a solid foundation to the upcoming research in the field.

**1.9. Contributions of the study**

The SLR’s primary purpose is to conduct a critical study of existing current methodologies to implement multi-fault diagnosis in industrial rotating machines to find solutions to the research question posed in Table 2 using PRISMA guidelines. From this analysis, the following are our significant contributions to the field:

The authors have tried to explain all the aspects needed to implement Multi-fault diagnosis in Rotating machines. The paper covers all



Fig. 5. General component-level faults in rotating machines.

the significant reviews on data sources from online datasets to building the test setup. The authors have also focused on sensor types and sensor selection. The paper has covered data acquisition details, including the hardware and the software. Signal processing is studied in detail with different features, including the time domain, frequency domain, and time–frequency domain features. The Paper also has briefed the aspects of multi-sensor data fusion, explaining the data level fusion, feature level fusion, and decision level fusion. The data-driven approach for predictive maintenance using different AI algorithms, the platforms to implement them are all systematically covered. Finally, the paper's primary focus is in conclusion, which gives the research gap and prospects that would guide future researchers in the field.

### 1.10. Paper organization

The paper organization is shown in Fig. 7. The paper has eight main sections: introduction, research methodology, review results, discussion, Challenges and limitations, future scope, and conclusion. The first section is the introduction explains the rotating machines, the significance of the study, the motivation behind the study, the terminology used, the evolution of maintenance strategy, multi-fault diagnosis, prior research, technology focus and evolution timeline for multi-fault diagnosis, research goal and contribution of the study. Section 2 is

the research methodology that explains the method used for PRISMA's systematic literature review. After the methodology comes the results Section 3, which is the paper's core that answers significant questions related to the multi-fault diagnosis in industrial rotating machines as formulated in Table 2. Next, we discuss the outcome of the survey in Section 4, followed by the challenges and limitations. One more important section in the paper is Section 5 which gives recommendations for future work with the research gap. Finally, we conclude the paper in Section 6, followed by references.

## 2. Research methodology

The procedures or strategies used to find, select, process, and analyze information about a topic are referred to as research methodology. A strategic review is carried out in this paper using the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines (Moher et al., 2009; Page et al., 2021). PRISMA is a set of guidelines for the structure and composition of systematic reviews and other data-driven meta-analyses. The systematic review presented in this paper has taken the PRISMA checklist table (Page et al., 2021), which has 27 items to be considered while using the PRISMA method for systematic review. This method comprises three steps: framing research questions, the search stage, and the standards for inclusion

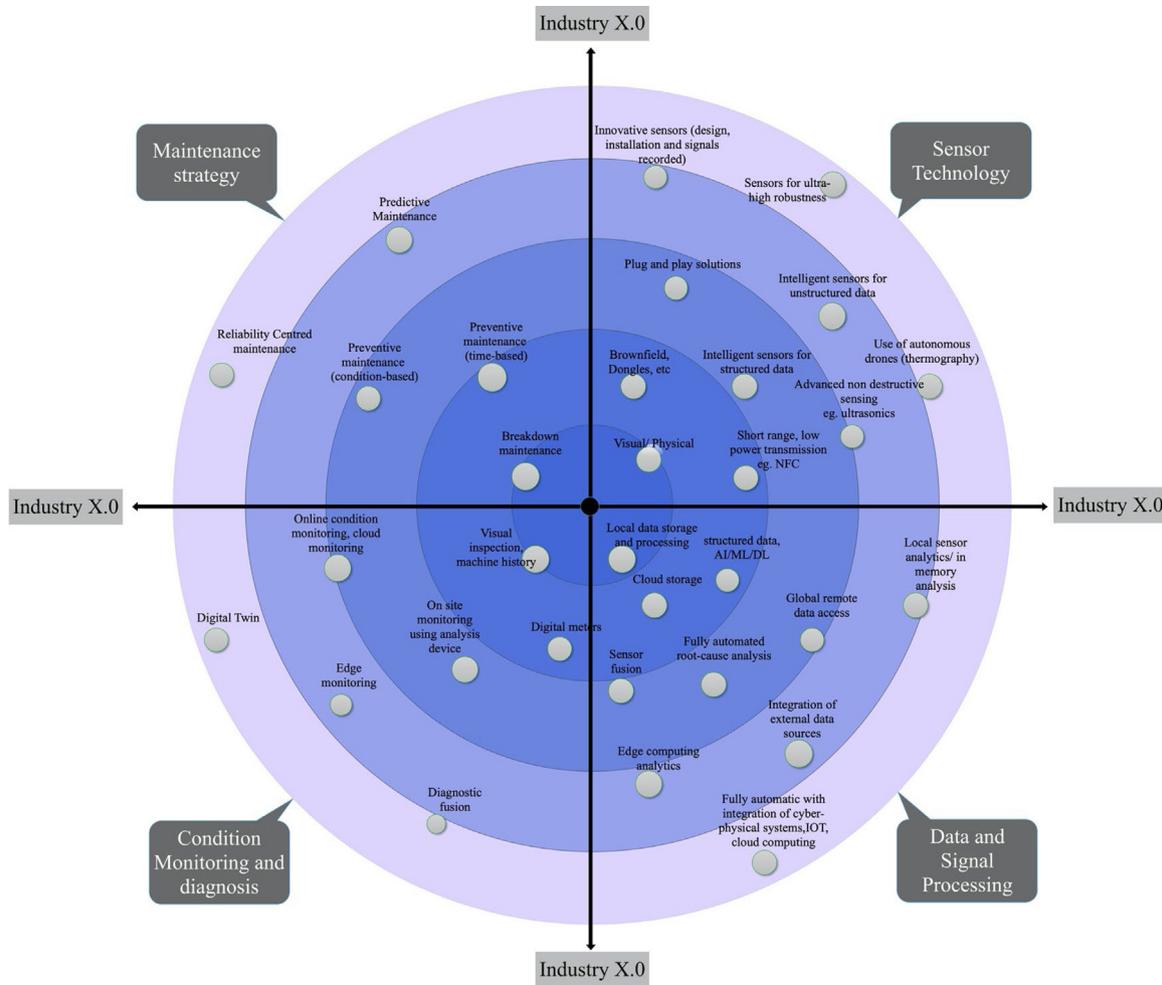


Fig. 6. Technology focus and evolution time-line for machine health monitoring.

Table 3

Keyword selection.

Parameter	Meaning	Keywords used
Population	It is an Application area	“Rotating Machines” OR “Bearings”
Intervention	It is the software methodology	“Artificial Intelligence” OR “Machine learning” OR “Deep Learning” OR “multi-sensor data fusion” OR “Multivariate.”
Outcome	It should relate to factors of importance to practitioners such as improved reliability, reduced production costs, and reduced time to market	“multi fault diagnosis” OR “Fault diagnosis” OR “multiple faults” OR “Fault detection”
Context	It is the context in which the intervention is delivered	“Rotating machines” OR “bearings”

and exclusion of research papers (Moher et al., 2009). The details of these three stages are explained below.

The first stage consists of formulating research questions which were shown in Table 2 earlier. The quality of research depends mainly on the research questions framed. Research questions guide us to explore different aspects of the research systematically. The second stage is the search for articles which starts with the identification of a database for articles. In this study, Scopus and Web Of Science (WOS) are used as the database for article selection. In this stage, Search fields are defined concerning the article title, abstract, and

keywords. Table 3 shows the selection procedure for keywords based on the PIOC (Population, Intervention, Outcome, Context) approach published by Kitchenham (Budgen and Brereton, 2006). The final set of keywords used is: (“Rotating Machines” OR “Bearings”) AND (“multi sensor data fusion” OR “Multivariate” OR “multi fault diagnosis” OR “multiple faults”).

The third and final stage is to create protocols for assessing the technical and scientific articles that these searches have generated from Scopus and WOS databases to keep only those most relevant articles to the research theme. The third stage is explained in detail in

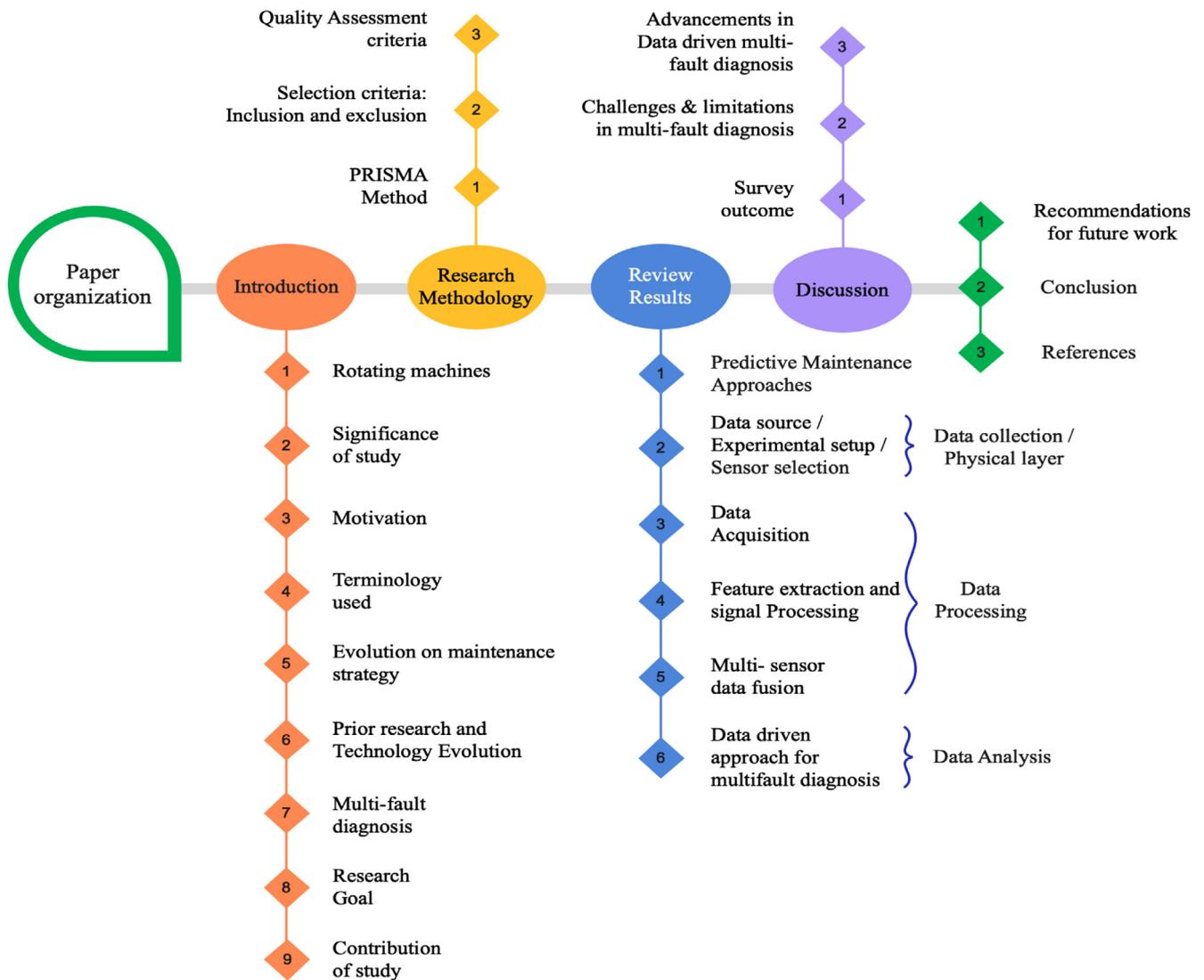


Fig. 7. Paper organization.

the following subsection, which mainly includes the inclusion criteria, exclusion criteria, quality assessment criteria, and their use for selecting or rejecting the paper.

### 2.1. Inclusion and exclusion criteria

A list of inclusion criteria for research paper selection and exclusion criteria for research paper rejection is applied to choose relevant research studies for systematic review. After applying the keyword query search in Scopus and WOS, these criteria are applied to the articles after the second stage. Inclusion and exclusion criteria applied are as shown in Table 4.

Out of all these criteria mentioned in Table 4, the most important criterion is to have the articles related to the research theme. To achieve this, three-stage assessment criteria applied are:

- Abstract-based Assessment: This includes reading the abstract to check whether the article is discussing our research theme. An abstract that matches at least 40% of the research theme is selected for further assessment: the full text-based assessment.
- Full text-based Assessment: This includes a complete reading of the article. Articles that match the research themes are selected, and those that do not match the research theme are rejected. The remaining articles go through the quality assessment.

- Quality-based Assessment: This criterion increases the quality of the literature review. To achieve this, quality assessment criteria are as discussed below.

### 2.2. Quality assessment criteria

The quality assessment is based on the following four criteria: The articles that do not meet these criteria are rejected.

- C1: Is the paper discussing multi-fault diagnosis in Industrial Rotating Machines?
- C2: Is the paper discussing data collection and related topics like sensor selection and sensor data fusion?
- C3: Is the paper discussing different feature extraction and signal processing methods?
- C4: Is the paper discussing the AI techniques related to fault diagnosis in rotating machines?

The pictorial explanation of the Systematic Literature Review process regarding PRISMA guidelines is shown in Fig. 8.

### 2.3. Systematic review implementation

The following main steps were used to select appropriate papers for this review. The Systematic review flow diagram using PRISMA

**Table 4**  
Inclusion and Exclusion criteria.

Sr. No.	Inclusion criteria
1.	Articles should be published between 2011 to 2021.
2.	Articles should meet at least one term related to the research theme.
3.	Articles should be either published or in the process of publishing in Journals.
4.	Articles should give answers to the research questions. Therefore, the title, abstract, and full-text reading are done to achieve this criterion.
Exclusion criteria	
1.	Non-English Literature.
2.	Duplicate articles.
3.	Articles with non-availability of full text.
4.	Articles not relevant to Fault Detection in Industrial Rotating machines.

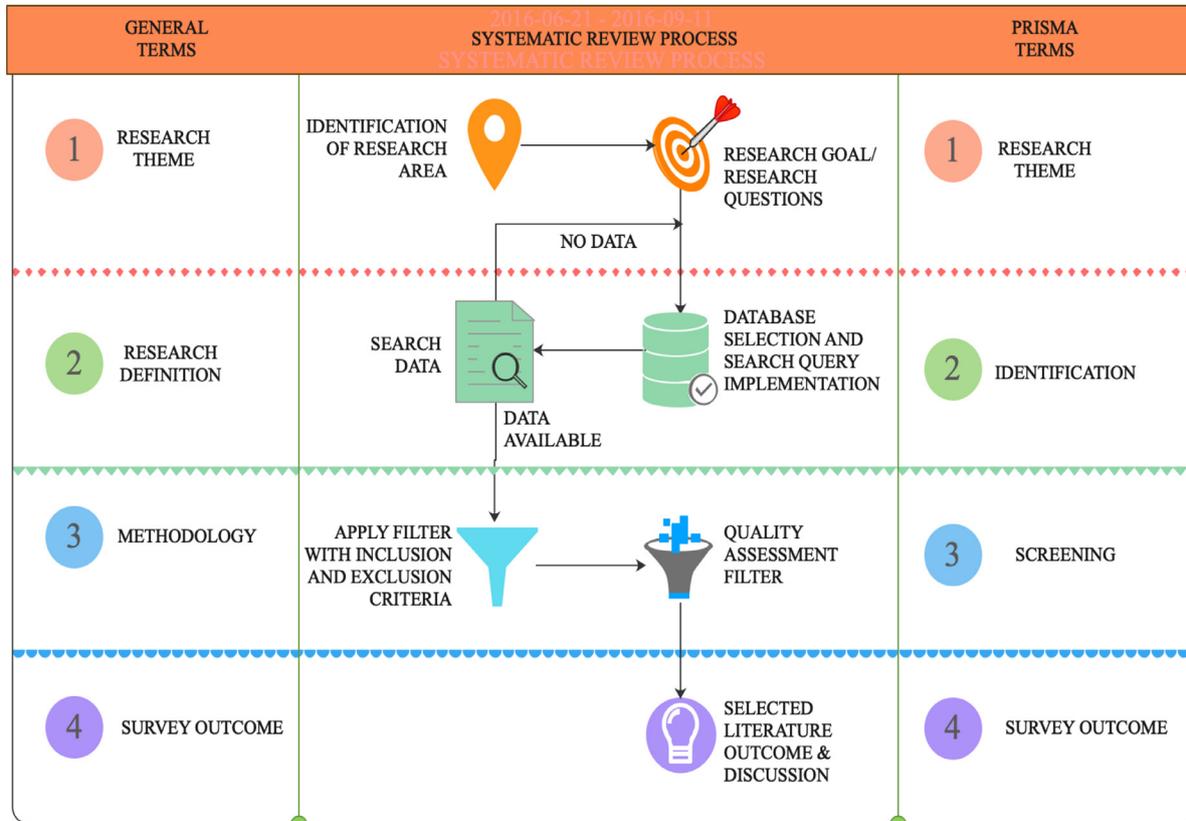


Fig. 8. Systematic literature review process.

guidelines, as shown in Fig. 8, depicts the steps of recognition, screening, eligibility, and inclusion. Fig. 9 depicts the systematic search strategy implemented. After formulating the research questions and the keywords for a search query, the next step is to select the database. Scopus and WOS were selected as the database, where initial search results were 2091 articles from Scopus and 261 articles from WOS. The next step was to implement the inclusion and exclusion criteria as discussed in Table 4. Accordingly, articles from 2011 to 2021 were selected. Also, articles in the English language were selected related to Engineering and computer science domain areas. Also, a filter was applied to select article-type documents and remove the documents from conference proceedings, review papers, etc. 116 documents from WOS and 1845 documents from Scopus were removed, and 391 articles were selected. The next step was to remove the duplicates. 97 duplicate articles were removed, leaving 294 total articles. The next stage was to apply a filter based on reading the titles of the articles, reading the abstract, and checking the scientific recognition of the articles. 192 misaligned articles were deleted, leading to 102 filtered articles. Also, it is essential to remove unavailable articles (full text). The final step is to read the whole article and discard the misaligned ones. 34

unavailable and misaligned articles were deleted. The final portfolio of articles comprised 68 closely aligned articles. This entire process is shown in Fig. 9.

### 3. Review results

This section summarizes the findings of our systematic review process. It answers the research questions formulated in Table 2 based on the review process results conducted using PRISMA guidelines. Here is the evaluation and summary of the papers.

#### 3.1. RQ1. What are the different approaches employed to achieve multi-fault diagnosis under Predictive Maintenance (PdM) for rotating machines in Industry?

Predictive maintenance (PdM) is a type of condition-based maintenance that monitors the condition of assets using sensor devices. These sensor devices supply data in real-time, which is used to predict faults using AI, and intimate when the asset will require maintenance and prevent equipment failure. Specific widely used parameters and

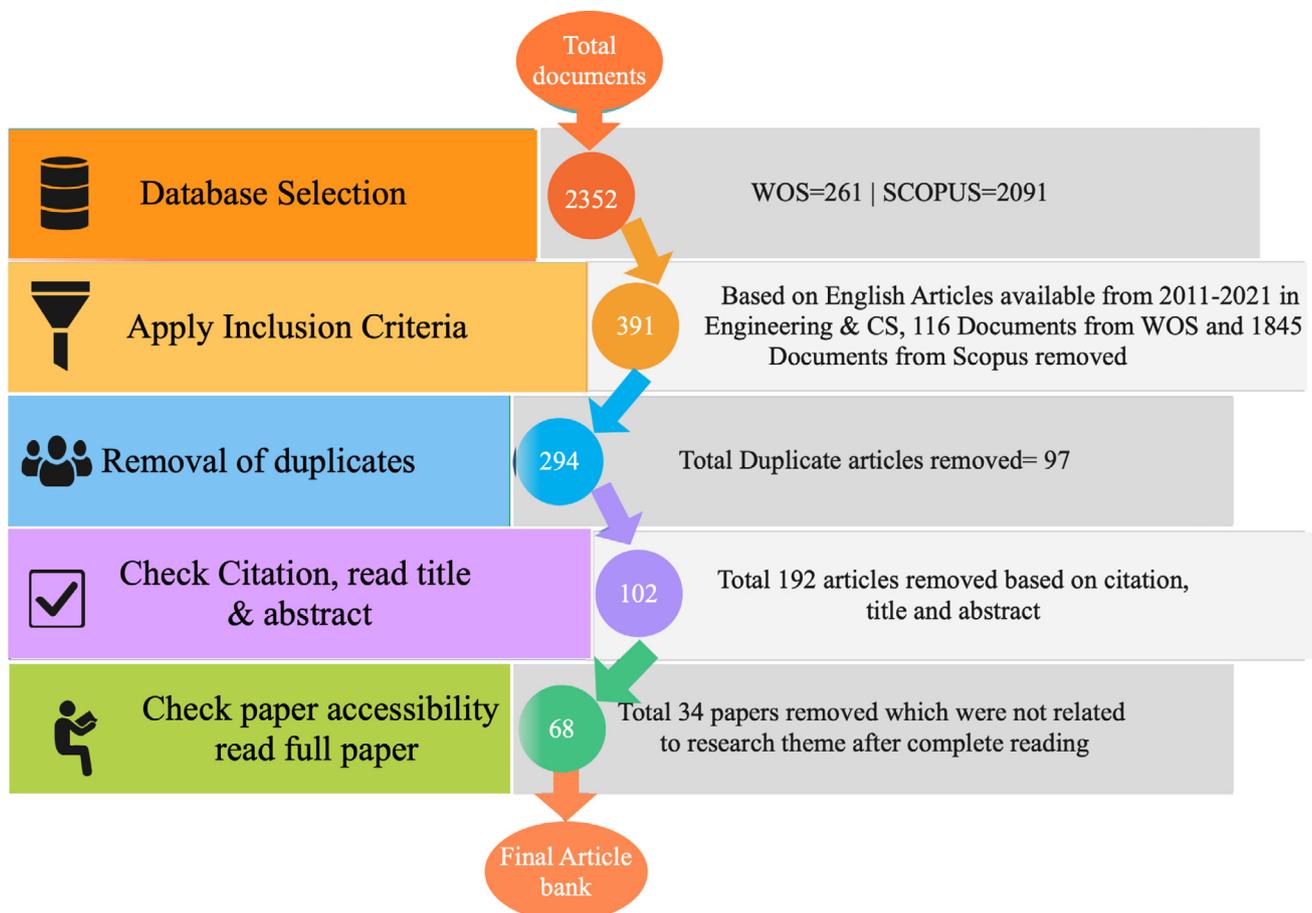


Fig. 9. Implementation of systematic literature review process.

methods (Mohanty, 2014) to detect the fault and predict the condition of Industrial rotating machines are Vibration analysis (Khadersab and Shivakumar, 2018), Motor Current Signature Analysis (Lee et al., 2015), Temperature analysis, Magnetic chip detectors (Tandon and Parey, 2006), Infrared Thermography, Acoustic Emission (Tandon and Parey, 2006), Airborne Ultrasound, Lubrication analysis, etc. A combination of these methods improves the accuracy of analysis to predict the faults. Fig. 10 (Gawde et al., 2022; AlShorman et al., 2020) depicts analysis of the different techniques used in condition monitoring.

The PdM approach is classified into three major categories: Physics-based Approach, Knowledge-based Approach, and Data-Driven Approach (Liao and Köttig, 2014; Valliani et al., 2019; Okoh et al., 2017). These approaches are summarized in Fig. 11 (Sayyad et al., 2021b). The knowledge-based approach (Liao and Köttig, 2014; Okoh et al., 2017) combines field experience and computational knowledge from domain experts and sets rules to interpret the faults. The advantage of this approach is that it requires less information and it does not require a mathematical model. However, it is challenging to implement it without historical data and domain expertise. Expert systems and fuzzy logic approaches are two examples of experience-based models that rely heavily on domain knowledge. Physics-based models (Zhao et al., 2013) are methods that use knowledge of a system's failure mechanisms (for example, unbalance growth) to create a mathematical equation model for the system's degradation process. The main advantage of this approach is that it does not require collecting a lot of data, and it can be easily validated. Extrapolation is also easily possible. However, at the same time, it is not suitable for complex processes or machines and requires expert knowledge. Also, considering all degradation mechanisms is a challenging task. These physics-based models include the Finite Element Model (FEM), Kalman filter (KF), and Particle filter (PF), which all rely heavily on mathematical models.

Data-driven models, the most widely used approach, depend highly on big data and analysis. The Analysis allows us to predict the system's condition or state or match comparable examples in the set of past experiences. The advantage of this approach is that it does not require a separate performance degradation process; however, it requires extensive data, and the accuracy depends highly on the algorithm's training. A data-driven approach (Shao et al., 2017; Jia et al., 2016; Udmale and Singh, 2019; Janssens et al., 2016; Jablon et al., 2020) is currently the trend attracting much attention of researchers. It mainly includes Artificial Intelligence models. Using different AI Algorithms, viz., Machine learning, deep learning is employed to build these models. Another effective and emerging approach that anchors the benefits of various currently available prognostics models is the hybrid approach (Swanson, 2001; Liu et al., 2012; Peel, 2008; Celaya et al., 2014). It combines different approaches (knowledge-based, physics-based, and data-driven) that result in a hybrid model with better predicting ability.

3.2. RQ2. What are the available data sources? How to select the appropriate sensors for data collection?

Condition monitoring and fault diagnostic research for rotating machines are critical for predictive maintenance, optimal device operation, and workpiece quality. Researchers are concentrating their efforts on two areas to increase this diagnostic accuracy: advanced signal processing technologies and artificial intelligence technology. The dilemma that emerges with the use and development of these new methods and techniques is that they have their benefits and drawbacks and can only be used in specific circumstances. As a result, the hybrid intelligent fault diagnostic technique has been extensively researched in

	METHODOLOGY	DEFINITION	APPLICATION/ ADVANTAGES	DISADVANTAGE
CONDITION MONITORING TECHNIQUES	VIBRATION ANALYSIS	Monitoring vibration pattern and detect abnormal event to evaluate condition monitoring	Applicable to almost all type of faults in rotating machines, Basic method, can be used for early Fault diagnosis	High cost for installation, updation and calibration, high sensor cost
	MOTOR CURRENT SIGNATURE ANALYSIS	Technique in which motor current readings are used to analyse in frequency domain	Used to detect faults in induction motors, Inexpensive	Sensitive to noise, Cannot be used as early Fault Diagnosis.
	TEMPERATURE ANALYSIS	Monitoring machinery condition based on temperature	Used to detect faults in bearings, motors, etc., Non-Intrusive	High Sensor cost, sensitive to noise, cannot be used for early fault diagnosis
	MAGNETIC CHIP DETECTORS	It detects ferromagnetic particles in fluid (oil) which can lead to engine failure	Used to detect faults in engine oil, fluids, Non-Intrusive	Low sensitivity, cannot be used for early fault diagnosis
	INFRARED THERMOGRAPHY	Detection of IR energy emitted by object and converted to thermal image to monitor condition	Used to detect faults in bearings, electrical machines, etc., Non-Intrusive	High sensor cost, cannot be used for early fault diagnosis
	AIRBORNE ULTRASOUND	Method of detecting leaks in steam process, gas, vacuums, compressed air systems	Used to detect faults in compressed air system	High sensor cost, Intrusive
	ACOUSTIC EMISSION/ ULTRASONICS	AE is transient elastic waves generated from release of strain energy due to deformation in structure	Used to detect faults in bearings, pump, gear, valve, etc.	High sensor cost, Intrusive, noise sensitive
	LUBRICATION MANAGEMENT	It is monitoring and managing lubrication levels in bearing, etc.	Used to detect bearing faults due to lubrication, lubrication oil faults	Expensive, effective for big size machines

Fig. 10. Condition monitoring techniques.

which multiple sophisticated signal processing methods and artificial intelligence approaches are used simultaneously. However, in most diagnostic systems, just one type of information (such as vibration information) is employed (Vargas-Machuca et al., 2020; Safizadeh and Latifi, 2014), resulting in inadequate machinery information, particularly in sophisticated systems. The lack of information even leads to misdiagnosis. Also, the extracted features are focused on a single domain, and features of other domains are ignored. Therefore, the diagnosis model must be based on multi-dimensional and multi-level information or data sources (Yan et al., 2016). When we think of Information or data source, there are three main aspects to it. One is the machinery/test setup on which the data is collected, the second is the sensors used for data collection, and the third is how to check the data validity. Let us analyze the different aspects implemented by different researchers.

### 3.2.1. Online data source

The data can be achieved in two ways. The first uses an online dataset, and the second uses a test setup to collect data using sensors. There are various online platforms available for online datasets. The most widely used dataset is provided by Case Western Reserve University (Neupane and Seok, 2020; Anon, 2018b). Ball-bearing test data for both normal and defective bearings are available on this page. Experiments were carried out with a 2 hp Reliance Electric motor, with acceleration data collected close and far from the motor bearings. The precise test settings of the motor and the bearing defect status for each experiment have been meticulously documented on these web pages. Electro-discharge machining was used to seed defects in motor bearings (EDM). Faults with diameters ranging from 0.007 to 0.040 inches were introduced at the inner raceway, rolling element (i.e., ball), and outer raceway individually. The test motor's faulty bearings were replaced, and vibration data was taken for motor loads ranging from 0 to 3 horsepower. The "FEMTO Dataset (Nectoux et al., 2012c)" is another popular dataset for estimating a bearing's remaining usable life (RUL),

which allows researchers to evaluate novel methods for bearing RUL prediction (Nectoux et al., 2012b). The FEMTO-ST2 institute designed and built PRONOSTIA, a platform for testing and verifying bearing fault detection, diagnostic, and prognostic techniques. One more dataset is the IMS bearing dataset (Lee et al., 2019), generated by the NSF/UCR Center for Intelligent Maintenance Systems (IMS) with support from Rexnord Corp. Unlike other datasets, which intentionally induce bearing defects by scratching or drilling the bearing surface or generating bearing faults by applying a shaft current for accelerated life testing, the IMS dataset provides a comprehensive natural bearing defect history record. The bearing is driven for 30 days in a row at a constant speed of 2000 rpm for 30 days (Lee et al., 2019). Another essential online dataset collection is available at NASA Prognostic Centre of Excellence (Iqbal et al., 2019; Lee et al., 2007). The Prognostics Data Repository collects datasets donated by universities, government organizations, and businesses. The data repository is dedicated to prognostic datasets, that is, datasets that may be utilized to create prognostic algorithms. Typically, these are time-series data from a nominal state to a failing state. The bearing dataset available on NASA PCoE is provided by the Center for Intelligent Maintenance Systems (IMS) (Lee et al., 2019), University of Cincinnati. NASA PCoE also has one more bearing dataset that is "FEMTO Dataset (Nectoux et al., 2012c)" discussed earlier. Another dataset available online is by the Society for Machinery Failure Prevention Technology (MFPT) (Anon, 2012), wherein they provide the Condition Based Maintenance Fault Database whose objective is to give multiple datasets of known good and faulty bearing and gear conditions. This dataset is being made publicly available, along with sample processing code, hoping that researchers and CBM practitioners would enhance the approaches and, as a result, develop CBM systems more quickly. One more platform that provides online datasets is Mendeley data (Huang and Baddour, 2018, 2019) which contains vibration signals collected from bearings of different health conditions under time-varying rotational speed conditions. There are 60 datasets in total in this. Next is IEEE DataPort (Li, 2022), a valuable and easily

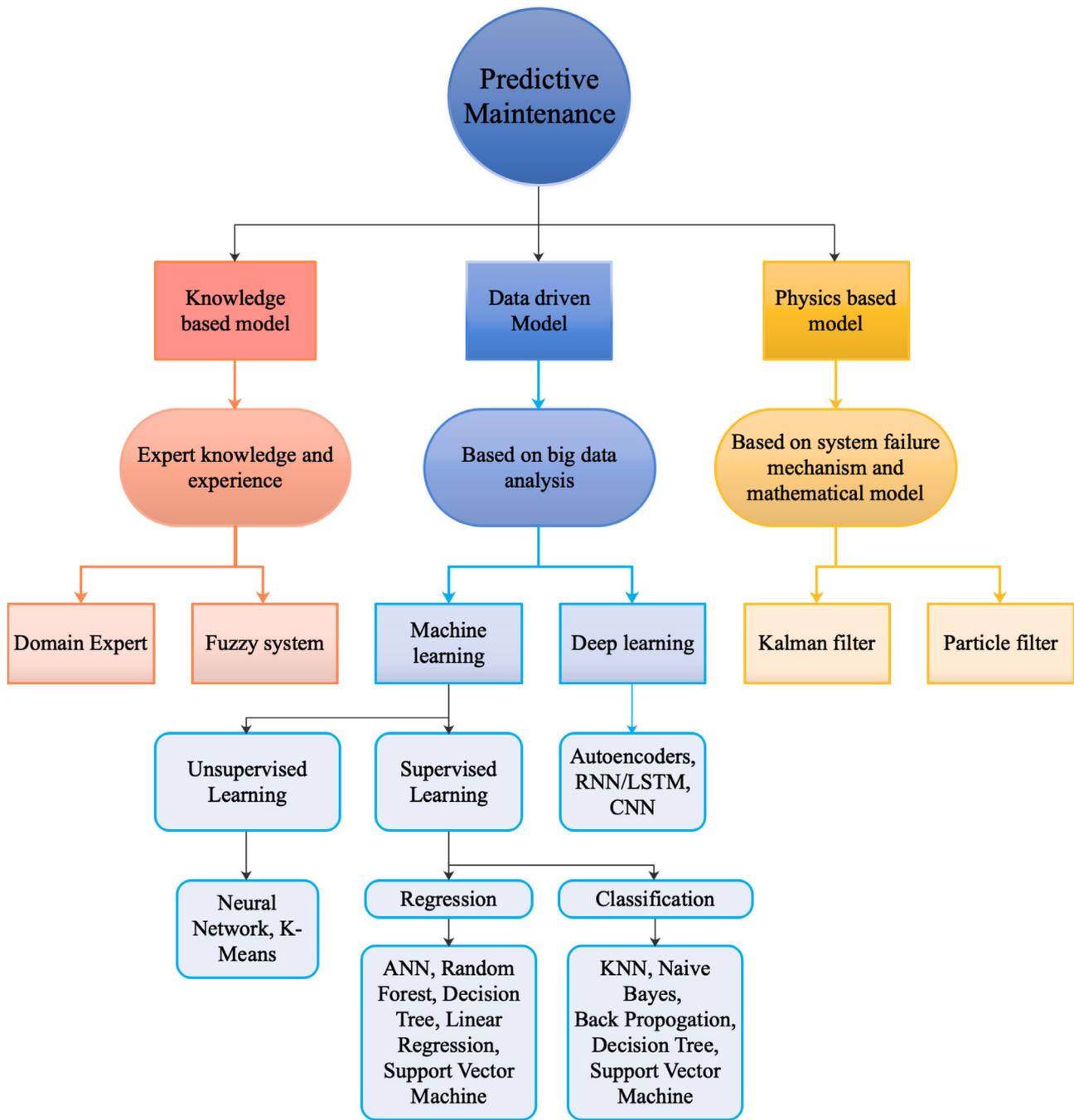


Fig. 11. Approaches to implement predictive maintenance.

accessible data platform that enables users to store, search, access, and manage standard datasets (Sayyad et al., 2022). Another bearing dataset (Kimotho et al., 2016) from Paderborn University comprises synchronous measurements of motor current and vibration signals, allowing multi-physics models to be verified and sensor fusion of various signals to improve bearing fault detection accuracy. Both stator current and vibration signals are measured with a high resolution, and a high sampling rate and experiments are performed on 26 damaged bearings and 6 undamaged (healthy) ones. Also, one more online dataset is composed of 1951 multivariate time-series acquired by sensors on SpectraQuest’s Machinery Fault Simulator (MFS) Alignment-Balance-Vibration (ABVT) (Anon, 0000a). It comprises six different simulated states: normal function, imbalance fault, horizontal and vertical misalignment faults and, inner and outer bearing faults. Table 5 (Zhang

et al., 2020) is a summary of all the available online datasets discussed above.

Having access to the online datasets gives monetary benefits as less expense is incurred in developing own test rig. Also, it saves time in making and designing a test setup. However, in the long run, it does not give data freedom. The test setups available online are for fixed conditions and a particular type of fault. If the researchers have to get more data for varied conditions, it is not possible. It can lead to incomplete diagnosis or misdiagnosis. Also, the datasets available online are mostly related to bearing faults. As a result, other significant faults in rotating machines are ignored, and multi-fault diagnosis is impossible. Also, one should check the authenticity of the data before using it in any project.

**Table 5**  
Summary of available online dataset for fault diagnosis of rotating machines.

Dataset	Sensor type	No. of sensors	Sampling frequency	Fault generation	Type of fault Speed	Motor data	Labeled	Load
CWRU (Anon, 2018b)	Accelerometer	2	12 & 48 Khz	Artificial (Single point faults using electro-discharge machining)	Bearing	1797–1720	Yes	0–3 hp
IMS (Lee et al., 2019)	Accelerometer	2	20 KHz	Natural	Bearing	2000	Partially labeled	6000 lbs
MFPT (Anon, 2012)	Not specified	–	97k SPS & 48k SPS	Natural	Bearing	–	Yes	270 & 300 lbs
MAFAULDA (Anon, 0000a)	Accelerometer, tachometer, microphone	4, 1 & 1	50 kHz	Artificial (Induced unbalance and misalignment)	Bearing, unbalance, misalignment	700–3600	Yes	–
Mendeley Data (Huang and Baddour, 2019)	Accelerometer, encoder for speed	1&1	200 kHz	Artificial (not mentioned)	Bearing	–	Yes	–
FEMTO (Nectoux et al., 2012c) Pronostia (Nectoux et al., 2012a)	Accelerometer, thermocouple	2 & 1	25.6 KHz	Natural	Bearing	–	No	4000N
Paderborn University (Kimotho et al., 2016)	Accelerometer	2	20 kHz	Natural	Bearing	1500 & 900	Yes	0.7 & 0.1 Nm
IEEE Data Port (Li, 2022)	This platform is a collection of datasets of different experiments conducted by different sources.							
NASA PCoE (Lee et al., 2007)	This platform is a collection of datasets of different experiments conducted by different sources.							

### 3.2.2. Offline data source using test setup

The online datasets, as discussed above, have their advantages as well as disadvantages. However, the biggest drawback is that one cannot study other faults in rotating machines using the available datasets. So though it might be a costly affair, indeed, the best option is to set up a test rig and collect data. Many researchers (Safizadeh and Latifi, 2014; Safizadeh and Golmohammadi, 2020; Su et al., 2015) opted for this option and successfully proved the results. So again, there are two options for the setup: design the test rig (Safizadeh and Golmohammadi, 2020) or buy the test rig online. Test setups by SpectraQuest, Inc. (Spectra Quest Inc, 0000) are widely used by most researchers (Su et al., 2015). Tyrannus Innovative Engineering & Research Academy is another platform that provides machinery fault simulators (TIERA Pvt Ltd, 0000). Collection of data should be ideally carried out on the real Industrial rotating machines. However, due to industrial protocols and uncontrollable conditions on the site, it is impossible to collect data directly from the Industrial environment. Hence the researchers came up with the machinery fault simulator model (Spectra Quest Inc, 0000). The model may have a different set of combinations of components, but what is shared is that there are two types of components: the driver and the driven type of rotating components that resemble the real-time industrial rotating machine behavior.

### 3.2.3. Sensor types and selection criteria

After setting up the test setup, knowing what type of sensors can be used for data collection is crucial (Hanly, 0000). Many sensors are available with different specifications, sensitivity, ranges, functions, applications, etc. Therefore, one needs to correctly choose the sensors considering different factors, as the sensors being the data collectors are the basis of the diagnosis (Guesmi et al., 2015). Sensor selection begins with an awareness of a machine's probable failure modes and

the related warning indications. Unbalance, bearing damage, cavitation (pumps), increased machine vibration levels, increased temperature of mechanical parts, loss or decrease of lubricant flow, and cooling water flow are typical warning signals in rotating machinery (Safizadeh and Latifi, 2014). Each of these warning signs can be analyzed and monitored using an appropriate sensor (Murphy, 2020). In this part, the sensors most often employed to identify problems in rotating machines (Kuntoğlu et al., 2021) at the earliest possible time, notably accelerometers and microphones, are discussed.

- **Accelerometer:** Accelerometers (Safizadeh and Latifi, 2014), as the name indicates, measure acceleration levels, typically expressed with the sign *g* (equivalent to gravity's acceleration, 9.81 m/s<sup>2</sup>). They are installed directly on the surface of (or within) the rotating machine near to bearings. Velocity or displacement may be more critical than absolute acceleration levels for specific applications, although this may be determined by integrating the acceleration data. Accelerometers are widely used in fault detection of rotating machines as they convey considerable information about machinery health (He et al., 2021b; Zhou et al., 2018; He et al., 2021c). A general rise in machine vibration is detected by basic vibration sensors, suggesting a potential machine problem. To detect faults with specific machine components like rolling element bearings or fan blades, more advanced sensors employ FFT (Fast Fourier Transform) signal processing to look at sensor data in the frequency domain (Kumar and Tiwari, 2021). Vibration sensors are classified into several categories, and one should be aware of the distinctions between them. Piezoelectric devices (Safizadeh and Latifi, 2014) rely on variations in electric current caused by movement. They frequently have a wide frequency response, high sensitivity, and low noise levels,

although costly. Because piezoelectric accelerometers have been around for a long time, several types are available for various purposes. Micro-electro-mechanical systems, or MEMS (Maruthi and Hegde, 2016), are tiny sensors frequently employed in IoT devices to detect vibrations. These sensors are frequently less expensive than Piezoelectric equivalents. An accelerometer may measure vibration in up to three directions. Movement from side to side, forward/backward, and up/down can all be perceived as vibrations. It always uses a 3-Axis sensor rather than a 1-Axis sensor since they are highly correlated, making it simpler to spot potential failures (Qian et al., 2019).

- **Eddy current sensor:** Non-contact Eddy-Current sensors (Safizadeh and Latifi, 2014) indicate a conductive component's position and/or change of position. Magnetic fields are used to operate these sensors. The sensor is equipped with a probe that generates an alternating current at its tip. Eddy currents are tiny currents created by the alternating current in the component we are measuring.
- **Temperature Sensor:** Temperature sensors (Lopez-Perez and Antonino-Daviu, 2017) detect changes in machine conditions in temperature by monitoring essential machine components. RTDs (Resistive Temperature Detectors) and thermocouples are utilized in direct measurement applications. Non-contact infrared sensors are utilized for indirect measuring applications.
- **Oil and Lubricant Sensor:** Particle pollution in lubrication systems is monitored using oil particle sensors (Safizadeh and Latifi, 2014). A rise in particle count may indicate that bearings, gear-boxes are wearing out. The key benefits of using these sensors are the ability to access lubrication conditions in harsh conditions and on machinery that is not easily accessible. Another advantage is establishing a better predictive and proactive maintenance program to detect the beginning stages of lubricating oil deterioration.
- **Current Sensor:** The current draw of machine components is monitored using current sensors (Guesmi et al., 2015). Monitoring the current draw of a motor is an example of a typical application. The high current drawn over time may indicate motor damage or any other problems arising in other parts of the machine. These sensors are clamped around the motor's electrical wire.
- **Acoustic Emission Sensor:** Acoustic emission sensor (Ferrando Chacon et al., 2015; Islam et al., 2019) is a device that transforms a local dynamic material displacement produced by a stress wave to an electrical signal. AE sensors are generally piezoelectric sensors with specific ceramic components such as lead zirconate titanate (PZT) as the main component. They are widely used to detect bearing faults.

Several static, dynamic, and other aspects must be considered when choosing a sensor to measure a physical parameter. Sensor selection changes based on the application area. Let us understand some key points to remember before buying a sensor concerning the multi-fault diagnosis of rotating machines.

First, it is crucial to consider the frequency response of the sensors chosen, especially concerning the accelerometer (Nishat Toma et al., 2021; Zhao et al., 2020b). It is perceived in terms of Hz in a vibration sensor. For example, if a sensor can detect vibrations between 1 and 10 Hz, it is difficult to identify the possible failure at 100 Hz. Table 6 (Tandon and Parey, 2006; Berry, 2000) summarizes the various vibration fault frequencies associated with some common rotating machinery faults. Before buying the sensor, one must check whether their fault frequencies lie in the sensor's frequency range. Next is the Accuracy of the sensor. The greatest difference between the real value and the measured value at the sensor's output is the accuracy of the sensor. Both an absolute value and a percentage of the whole scale can be used to represent accuracy.

Next is the sensitivity of the sensor. Industrial accelerometers generally have a sensitivity of 10 to 100 mV/g (Islam et al., 2019), although

greater and lower sensitivity options exist (Khadersab and Shivakumar, 2018; Nishat Toma et al., 2021). A low sensitivity (10 mV/g) sensor is preferred if the machine produces significant amplitude vibrations (more than 10 g RMS) at the measuring location. For, e.g., a 100 mV/g sensor should be utilized if the vibration is less than 10 g RMS. The highest g level should never surpass the sensor's acceleration range. One should also note the temperature range of the sensor. Sensors must be able to withstand the application's temperature extremes. While deciding about the sensor, it is also essential to study the type of data acquisition (DAQ) hardware needed, ignorance of which can be a very costly affair. The sensor interface is crucial because it is the medium to connect to the DAQ. One should also choose between wired and wireless sensors. Wired sensors are always preferred because the data is reliable. Mounting of the wired and wireless sensors (Gao et al., 2006) is also to be checked. There are four types of mounting, with threaded studs being the best, followed by adhesives, magnets, and probe tips. One more critical factor is the computing technique. Whether edge computing will be implemented or cloud computing will be preferred. Nowadays, the processing is done at the network's edge (Qian et al., 2019) rather than on cloud servers, which reduces system response time, transmission bandwidth use, cloud storage, and computation resources. This is also an essential factor as a slight error in any decision can lead to monetary losses. Table 7 (Murphy, 2020) summarizes sensor characteristics and some of the problems they can detect. The table also includes an overview of the most common faults associated with rotating machines and corresponding sensor requirements. Table 8 gives an analysis of multiple sensors used by researchers in their experimental setup.

#### 3.2.4. Challenges concerning smart sensors in Industry 4.0:

- The first challenge is related to sensor fusion. Sensor fusion is a technology that combines data from multiple sensors to create a single data point. A sensor fusion algorithm integrates sensor outputs with the highest accuracy and efficiency while consuming the least power and reduced noise. Furthermore, these sensors communicate with an application processor via a sensor hub, and selecting appropriate peripherals for each sensor is critical to the success of sensor-fusion systems.
- The next is the challenge related to security and privacy. Several solutions, both hardware, and software are aimed at resolving privacy and security concerns. The industries would never want their data going out of the organization, especially in cloud computing.
- In a given industry, more than one sensor might be sending data over the same network. As a result, the network traffic increases, resulting in data loss.
- Finally, it is also vital to have an energy-efficient sensor network.

#### 3.3. RQ3. What are the different data acquisition methods? What are the data validation techniques?

Data acquisition is a critical step in condition monitoring (CM) of rotating machinery (Soto-Ocampo et al., 2020). The Data Acquisition System (DAQ) characteristics and the price they represent are significant challenges in their implementation (Kumar et al., 2022b). The analog signal from an accelerometer must be converted to a digital signal and recorded once it has been appropriately conditioned. The data acquisition stage involves gathering measurement data from the sensors and processing the raw signal to extract relevant features that may be used to determine the system's health. In data science, this latter process is referred to as feature engineering discussed in upcoming sections.

**Table 6**  
Fault frequency and phase corresponding to different faults in rotating machines.

Fault	Fault frequency (fr = RPM/60) of driver or driven rotating machine	Phase	High vibration axis
Force unbalance	fr	90° (between horizontal and vertical)	Radial (horizontal)
Couple unbalance	fr	180° out of phase (across the bearings)	Radial
Static unbalance		0° out of phase (across the bearings)	
Dynamic unbalance	fr	In between 0° to 180° (across the bearings)	Radial
Overhung rotor unbalance	fr	90° (between horizontal and vertical) 180° axial phase diff.	Radial and Axial
Angular misalignment	fr, 2fr, 3fr	180° out of phase across the coupling	Axial
Parallel misalignment	fr, 2fr, 3fr	180° out of phase across the coupling	Radial
Misaligned bearing cocked on the shaft	fr, 2fr, 3fr	180° out of phase on bearing housing	Axial
Rolling element bearing	Rolling element fault frequency is given by:  Outer race defect = $\frac{N}{2} fr \{1 - \frac{Rd}{Pd} \cos \alpha\}$ Inner race defect = $\frac{N}{2} fr \{1 + \frac{Rd}{Pd} \cos \alpha\}$ Rolling Element defect = $\frac{Pd}{Rd} fr \{1 - (\frac{Pd}{Rd} \cos \alpha)^2\}$ Cage Defect Frequency = $\frac{fr}{2} \{1 \pm \frac{Rd}{Pd} \cos \alpha\}$ (+ sign if the outer race is rotating, - sign if the inner race is rotating N = No. of rolling elements, Fr = shaft rotational speed, Hz, Rd = Rolling element diameter, Pd = Pitch circle diameter, α = Contact angle	-	Axial
Eccentric rotor	fr (of motor and driven machine, e.g., Fan)	Either 0° or 180° (between horizontal and vertical)	Radial
Bent shaft	fr (if bent near shaft) 2fr (if bent near coupling)	180° axial phase difference	Axial
Mechanical looseness	fr (structural looseness at machine feet)	90° or 180° (between horizontal and vertical)	Radial (Vertical)
	0.5fr, fr, 2fr, 3fr (pillow block bolt looseness)	-	Radial
	0.5fr, fr, 1.5fr, 2fr, 2.5fr,... etc. (improper fit between components)	-	Radial
Resonance	When fr = natural frequency of components	Before and after resonance, a shift in phase difference is 180°	Radial
Soft foot	fr (also can be at 2fr, 3fr, 2 times line frequency..)	-	Radial (vertical)
Gear faults	Tooth meshing frequency = Nfr And sidebands at Nfr ± kfr, N: Number of gear teeth, K = 1, 2, 3..	-	Radial

3.3.1. DAQ setup specifications

Following criteria are very important when researching data acquisition hardware for a given application (Hanly, 0000).

**Sensor compatibility:** The type of appropriate data acquisition system is typically determined based on the sensor’s output. Some questions related to sensor compatibility that generally arise are whether the sensor output is analog or digital, the output range, etc. In addition, the sensor must be compatible with the data acquisition system.

**Sampling Frequency:** According to the Nyquist theorem, the sampling frequency (inverse of the sampling rate) should be at least 2.56 times the maximum frequency present in the signal to catch the vibration signal’s profile (Hanly, 0000) accurately. Picking a system that can sample at least ten times faster than the fastest signal that needs to be recorded is a valuable piece of advice (Islam et al., 2019).

**Measurement Resolution:** The resolution is usually provided in bits, converted to acceleration units to compute the resolution. Consider an accelerometer system with a 24-bit resolution, which means it can measure 24 (Tandon and Parey, 2006; Kumar and Tiwari, 2021; Khalastchi and Kalech, 2018) acceleration levels. DAQ systems usually

have a resolution of 16 or 24 bits. Higher the resolution better the data visualization. One must note the difference between resolution of DAQ system and the resolution of the sensor used. Both may vary. Sometimes the sensor may have a very high resolution however the DAQ system might have comparatively lower resolution. In this case, the data acquired may be of the lower resolution as compared to the resolution of the sensor.

**Filtering capabilities:** Filtering is an essential function of DAQ used to filter unwanted frequency components or noise. Type of filter used changes from one application to other.

**Dynamic Range of DAQ System:** The variation between the smallest and biggest visible parts of a signal is known as a dynamic range. Systems with greater dynamic ranges improve vertical axis resolution. Most applications can be handled by having a dynamic range higher than 100 dB and a sampling rate of at least 200 kS/s.

**Standalone or PC connection:** PC-connected DAQ systems have the advantage of being smaller as there is no need for separate displays,



There are different data acquisition options, including Data loggers, Data Acquisition devices, and Data Acquisition systems. A Data Logger is a self-contained data collection system with an integrated CPU and pre-programmed software. Data loggers are popular because they are portable and easy to use for specialized purposes and may function as stand-alone devices. A data acquisition device (Khadersab and Shivakumar, 2018) (USB, Ethernet, PCI, etc.) has signal conditioning and an ADC, but it cannot operate without being linked to a computer (Soto-Ocampo et al., 2020). Plug-in device users can use either preconfigured data acquisition software (Zhao et al., 2020b), such as DAQamiTM, or a programming environment, such as PythonTM, C++, DASyLab, MATLAB, and LabVIEW TM. Data collection devices provide a configurable solution for a specific application, with various BUS choices (Soto-Ocampo et al., 2020) and the ability to utilize your favorite software. Modular data acquisition systems are developed for complicated systems that require several sensor types to be integrated and synchronized. These systems are more challenging to set up and operate, but they are very adaptable. Although modular data acquisition systems are the most expensive choice, many applications require the functionality that only a data acquisition system can provide. The DAQ's last component is a computer that collects all of the data collected by the DAQ hardware for further processing. To make sense of the data, DAQ software is also essential to generate legible and relevant results. To put it another way, the DAQ software serves as a bridge between the user and the DAQ hardware.

### 3.3.3. Types of DAQ systems

There are different types of DAQ Systems. Wireless DAQ Systems (Kurnyta-Mazurek et al., 2020), Serial communication DAQ Systems, USB DAQ Systems, and DAQ Plugin boards (Omega Engineering inc, 0000). Wireless systems consist of wireless transmitters sending data back to a wireless receiver connected to a remote computer. When the measurement needs to be conducted at a distance from the computer, serial communication data acquisition systems are an excellent alternative. There are numerous communication protocols (Luo et al., 2019), the most popular being RS232, which allows for up to 50 ft of transmission lengths. RS485 outperforms RS232 and allows for transmission lengths of up to 5000 ft. USB is a new protocol for connecting PCs to data acquisition devices. Because USB interfaces provide power, the data acquisition system only requires one cable to connect to the PC. Data acquisition boards for computers are directly connected to the computer bus. The advantages of utilizing boards include speed (because they are simply linked to the bus) and cost (because the computer provides the cost of packaging and power).

### 3.3.4. Data validation

Data validation is a critical process that ensures the quality of input data before it is utilized to build models and insights (Polyzotis et al., 2019). Whether collecting data in the field, analyzing data, or preparing to deliver data to stakeholders, data validation is crucial for every data handling activity. If the data is not accurate from the start, findings will most likely be inaccurate as well. As a result, data must be verified and validated before being used. The data validation procedure includes several steps:

- Ensure that the data is of the correct type: integer, data, text, Boolean, and so on.
- Checking the value range: minimum and maximum values, as well as correct format (voltage, acceleration, etc.)
- Validating data by applying application-specific requirements such as correct temperature, etc.
- Checking for consistency: It is important to check the consistency of the data. For eg. In case of Unbalance fault in the machinery, vibration amplitude for horizontal measurement is always higher than axial and vertical, and so on.

Writing a script for data validation may be an option depending on coding language proficiency. Another option is to use software programs designed for data validation. Because AI and machine learning models can only generate legitimate results if constructed with valid data, it is essential to follow all of the procedures outlined above during the data acquisition phase to guarantee that models work with clean data.

### 3.4. RQ4. What are the different signal processing techniques?

Vibration signals recorded using vibration sensors from a rotating machine are frequently in the time domain. Depending on the type of sensor used to acquire the data, they are a collection of time-indexed data points gathered across historical time, signifying acceleration, velocity, or proximity (Time Domain Analysis, 2019). This data is so extensive and from multiple sources in multiple conditions that it is challenging to inspect and conclude the type of fault visually. As a result, Signal processing is frequently required to clean data and put it into a format from which condition indicators may be extracted, called features. Feature extraction is a part of signal processing that gives the essence of the data. These features are used to distinguish between two different vibration signals. Feature extraction is a dimensionality reduction method that reduces a large collection of raw data into smaller groupings for processing (Huang and Liu, 2020). Feature extraction refers to strategies for selecting and/or combining variables into features to reduce the quantity of data that must be processed while still thoroughly and adequately characterizing the original data set (Kumar and Kumar, 2019). The speed of learning and generalization phases in the machine learning process is aided by reducing data and the computer's efforts in creating variable combinations (features). The feature extraction is classified under three categories: time-domain features, frequency domain features, and time-frequency domain features (Li, 2006; Huang and Liu, 2020; Li et al., 2016). Let us understand the different features in detail.

#### 3.4.1. Time-domain features

A time-domain graph shows how a signal changes over time. Let us look at statistical functions and other sophisticated approaches that may be used to extract features from time-indexed raw vibration datasets. It will adequately reflect machine health to better comprehend vibration signal processing in the time domain. Different statistical functions are used to extract features from time-domain signals based on the amplitude (Time Domain Analysis, 2019). Statistical Time domain features (Islam et al., 2019) are Peak Amplitude, Mean Amplitude, Root Mean Square (RMS) Amplitude, Peak to Peak Amplitude, Crest Factor (CF), Variance and Standard Deviation, Standard Error, Zero Crossing, Wavelength, Wilson Amplitude, Slope sign change, Impulse factor, Margin factor, Shape factor, Clearance factor, Skewness, Kurtosis, Higher-Order Cumulants, Histogram, Entropy (Wei et al., 2019; Biggio and Kastanis, 2020). Time Synchronous averaging features include TSA signal, Residual Signal (RES), and Difference Signal (DIFS). Time series regressive models include Auto-Regressive Model (AR Model), MA Model, ARMA Model, ARIMA Model. Filter-based methods include demodulation, the Prony model, and adaptive noise cancellation (ANC). Stochastic parameters such as chaos, correlation dimensions, and thresholding methods, i.e., soft and hard threshold, are considered effective techniques for analyzing time-series vibration signals. Furthermore, the Blind source separation (BSS) is a signal-processing method that recovers the unobserved signals from a set of observations of numerous signal combinations. All these methods and are shown in Fig. 12 (Nandi and Ahmed, 2019). Detailed analyses of some of these time-domain features, along with their definition and formula, are given in Table 9 (Huang and Liu, 2020; Nandi and Ahmed, 2019).

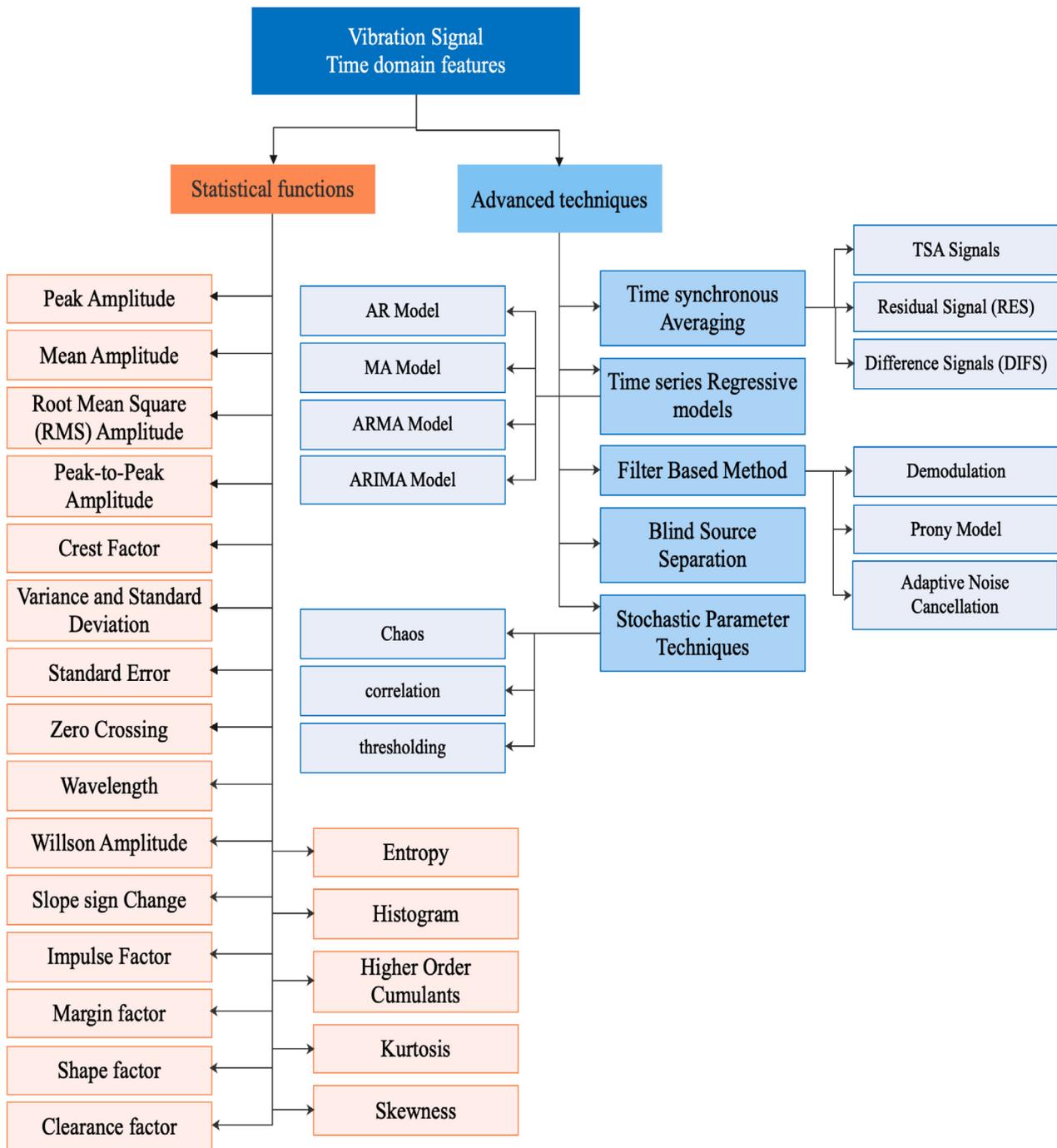


Fig. 12. Overview of time domain feature extraction methods.

3.4.2. Frequency domain features

One of the most often used vibration analysis techniques for monitoring equipment is frequency analysis, also known as spectrum analysis. In the frequency domain, each sine wave will be represented as a Spectral component. Frequency domain analysis methods, in reality, can reveal information based on frequency features that are difficult to detect in the time domain (Nandi and Ahmed, 2019). As discussed earlier, vibration signals in the time domain are generated by rotating machines. To convert them into the frequency domain, we use Fourier analysis. There are different types of Fourier analysis like Discrete Fourier Transform (DFT), Fast Fourier Transform (FFT), Inverse FFT and DFT, etc. (Sohaib et al., 2017), which are used to transform the time-domain signal to the frequency domain. Apart from this, several other approaches for extracting various frequency spectrum features

may be utilized to depict a machine’s health effectively. The other approaches include Envelope spectrum analysis, power spectrum analysis, spectral kurtosis (Touzout et al., 2020), spectral skewness, Spectral Entropy, Shannon Entropy (Chhetri and Faruque, 2020), and some Higher-order spectrum analysis. There are also statistical functions like Arithmetic mean, Geometric mean, Frequency Centre (FC), RMS Frequency (RMSF) (Islam et al., 2019), Root variance frequency (RVF), median frequency, etc. When a failure occurs, the frequency element changes, and so do the FC, RMSF, and RVF values. The FC and RMSF represent the main frequency position changes, whereas the RVF depicts power spectrum convergence. All these methods and are shown in Fig. 13 (Huang and Liu, 2020; Kumar and Kumar, 2019; Nandi and Ahmed, 2019; Caesarendra and Tjahjowidodo, 2017). Detailed analyses of some of these frequency domain features, along with their definition

**Table 9**  
Time domain features along with their definition and formula.

Feature	Definition	Formula	Significance/Note
Peak amplitude	Largest positive amplitude of the vibration signal. Indicator of occurrence of impacts.	$x_p = \frac{1}{2} [x_{max}(t) - x_{min}(t)]$	$x$ = amplitude $x(t)$ = vibration signal. Peak amplitude is valuable for shock events, but it does not consider the time duration or energy in the event.
Mean amplitude	Average of the vibration signal throughout a measured interval.	$\bar{x} = \frac{1}{T} \int x(t) dt$	$T$ = sampled signal duration.
Root Mean Square (RMS) amplitude	Variance of the vibration signal magnitude. It is the measure of power contained in the vibration signal.	$x_{RMS} = \sqrt{\frac{1}{T} \int  x(t) ^2 dt}$	It increases as fault develops.
Peak-to-peak amplitude	Difference between the highest positive peak amplitude and the highest negative peak amplitude.	$x_{p-p} = x_{max}(t) - x_{min}(t)$	Provides max. excursion of the wave, beneficial wrt. Displacement, specifically clearances.
Crest factor	Ratio of the vibration signal's peak amplitude to its RMS amplitude. Faults often first manifest themselves in changes in the peakiness of signal before they manifest in energy represented by RMS.	$x_{CF} = \frac{x_p}{x_{RMS}}$	Healthy bearing = more CF. Calculates how much impact occurs during the rolling element and raceway contact. CF can provide early warning for faults when they first develop.
Variance and standard deviation	Variance is the deviation of the vibration signal energy from the mean value. The square root of the variance is the standard deviation.	$(V) \sigma_x^2 = \frac{\sum (x_i - \bar{x})^2}{N-1}$  $(SD) \sigma_x = \sqrt{\frac{\sum (x_i - \bar{x})^2}{N-1}}$	$N$ = no. of sampled points $x_i$ = element of $x$ .
Impulse factor	The ratio of the peak value to the average of the absolute value of the vibration signal.	$x_{IF} = \frac{x_{peak}}{\frac{1}{N} \sum_{i=1}^N  x_i }$	Compare the height of a peak to the mean level of the signal.
Clearance factor	Ratio of the maximum value of the input vibration signal to the mean square root of the absolute value of the input vibration signal.	$x_{CLF} = \frac{x_{max}}{(\frac{1}{N} \sum_{i=1}^N \sqrt{ x_i })^2}$	This feature is max. for healthy bearings and decreases for the defective ball, outer race, and inner race, respectively. CF has the highest separation ability for defective inner race faults.
Skewness	The measure of asymmetrical behavior of vibration signal through its probability density function (PDF), i.e., it measures whether vibration signal is skewed to left or right side of distribution of normal state of the vibration signal.	$x_{SK} = \frac{\sum_{i=1}^N (x_i - \bar{x})^3}{N \sigma_x^3}$	$x_{SK}$ For normal condition is zero. Faults can impact distribution symmetry and therefore increase the level of skewness.
Kurtosis	The measure of the peak value of the input vibration signal through its PDF.	$x_{KURT} = \frac{\sum_{i=1}^N (x_i - \bar{x})^4}{N \sigma_x^4}$	Good bearing: Kurtosis value $< 3$ . defective bearing: Kurtosis value $> 3$ .
Histogram	Discrete PDF of the vibration signal.	$LB = x_{min} - 0.5(\frac{x_{max} - x_{min}}{N-1})$  $UB = x_{max} - 0.5(\frac{x_{max} - x_{min}}{N-1})$	The lower bound (LB) and upper bound (UB) are two characteristics derived from the histogram.
Entropy	Measure of the uncertainty of probability distribution of the vibration signal.	$x_{ENT} = \sum_{i=1}^N p_{x_i} \log p_{x_i}$	$p_{x_i}$ = probabilities computed from the distribution of $x$ .
AR model	Linear regression analysis of the current signal values, i.e., the estimated signal values, of the vibration time series against previous values of the time series.	$x_t = a_1 x_{t-1} + a_2 x_{t-2} + \dots + a_p x_{t-p} + \mu_t$ $\mu_t = \mu_t + \sum_{i=1}^p a_i x_{t-i}$	$x_t$ = stationary signal, $a_1 - a_p$ are model parameters, $\mu_t$ = white noise $p$ = model order.

and formula, are given in Table 10 (Huang and Liu, 2020; Kumar and Kumar, 2019; Nandi and Ahmed, 2019; Caesarendra and Tjahjowidodo, 2017).

3.4.3. time–frequency domain features

Rotating machines, in general, generate stationary vibration signals. However, some rotating machine analysis is focused on analyzing vibrations during a speed change. As a result, nonstationary signals with changing frequency content are common. When we convert a signal to its frequency domain, we assume that its frequency components do not vary over time, i.e., the signal is stationary. As a result, the Fourier transform in the frequency domain cannot offer information on the time distribution of spectral components. Therefore time–frequency domain needs to be used for nonstationary waveform

signals, which are very common when there is machinery failure (Nandi and Ahmed, 2019). Standard time–frequency domain analysis techniques include Short-time Fourier transform, Wavelet analysis, Empirical mode decomposition (Wang et al., 2017), Hilbert–Huang Transform, Wigner–Ville distribution, Local Mean Decomposition, Kurtosis, and Kurtogram (Tang et al., 2020; Gangsar and Tiwari, 2018), etc. These techniques convert one-dimensional time-domain signals into a two-dimensional time–frequency function (Feng et al., 2013). All these methods and are shown in Fig. 14 (Huang and Liu, 2020; Nandi and Ahmed, 2019). Detailed analyses of some of these frequency domain features, along with their definition and formula, are given in Table 11 (Huang and Liu, 2020; Nandi and Ahmed, 2019; Feng et al., 2013). Also, the literature analysis of some of the articles related to feature evaluation is shown in Table 12.

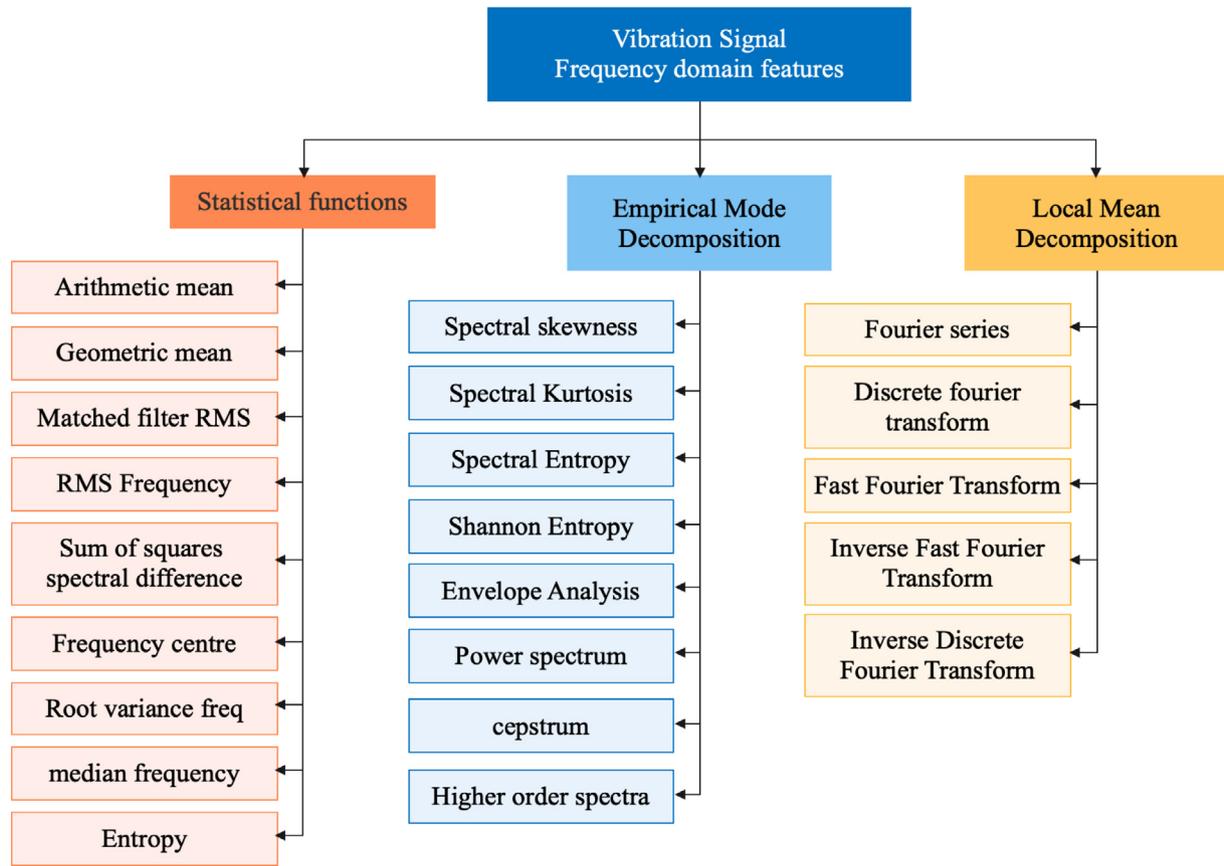


Fig. 13. Overview of frequency domain feature extraction methods.

Table 10  
Frequency domain features along with their definition and formula.

Feature	Property	Formula	Note/Significance
Discrete Fourier Transform	Used to convert time domain signal to the frequency domain	$x(u) = \int_{-\infty}^{\infty} x(t)e^{-j\omega t} dt$	$\omega = 2\pi/T$ It can be used to find the root of the fault.
Frequency Center	Indicate the position changes of main frequencies	$FC = \frac{\sum_{i=1}^N x_i^2 x_i}{\sum_{i=1}^N x_i^2}$	-
RMS Frequency	Indicate the position changes of main frequencies	$RMSF = \sqrt{MSF}$	$MSF = \frac{\sum_{i=1}^N (x_i^2)^2}{4\pi^2 \sum_{i=1}^N x_i^2}$ Represents overall level of energy across freq. range
Root Variance Frequency	Shows the convergence of the power spectrum	$RVF = \sqrt{MSF - FC^2}$	-
Spectral Skewness	SS measures the symmetry of the distribution of spectral magnitude values around its mean.	$SS(n) = \frac{2 \sum_{k=0}^{B_L} ( X(k,n)  - \mu X )^3}{B_L \cdot \sigma_{ X }^3}$	-
Spectral Kurtosis	Measures the distribution of the spectral magnitude values and compares them to a Gaussian distribution	$SK(n) = \frac{2 \sum_{k=0}^{B_L} ( X(k,n)  - \mu X )^4}{B_L \cdot \sigma_{ X }^4} - 3$	-

3.5. RQ.5. What are the approaches to achieve information fusion or multi-sensor data fusion?

Predictive maintenance has currently been the trend of Industry 4.0, where the machine is monitored for early detection of the fault and avoid failure before it occurs. A single sensor focuses on one parameter avoiding the broader aspects of data, thereby degrading the data quality and likely to induce error in monitoring complex equipment. Hence, multiple sensor configuration technology is introduced to collect extensive information of a machine to enhance monitoring capabilities in terms of measurement accuracy and data richness to improve precision,

resolution, efficiency, robustness, and reliability of the entire system. However, complex data collected by multiple sensors create a challenge for data integration and analysis. Therefore, Multisensor data fusion techniques are in great demand for future applications (Yi et al., 2018). The advantage of multi-sensor data fusion is that sensor data collected from several locations span a broader display range of the actual situation at the machinery. Also, the complete examination of each sensor's data complements the information while reducing discrepancies. It also increases the data credibility (Tang et al., 2020). Information fusion technology can be divided into three fusion methods: data-level fusion, feature-level fusion, and decision-level fusion. Each fusion method

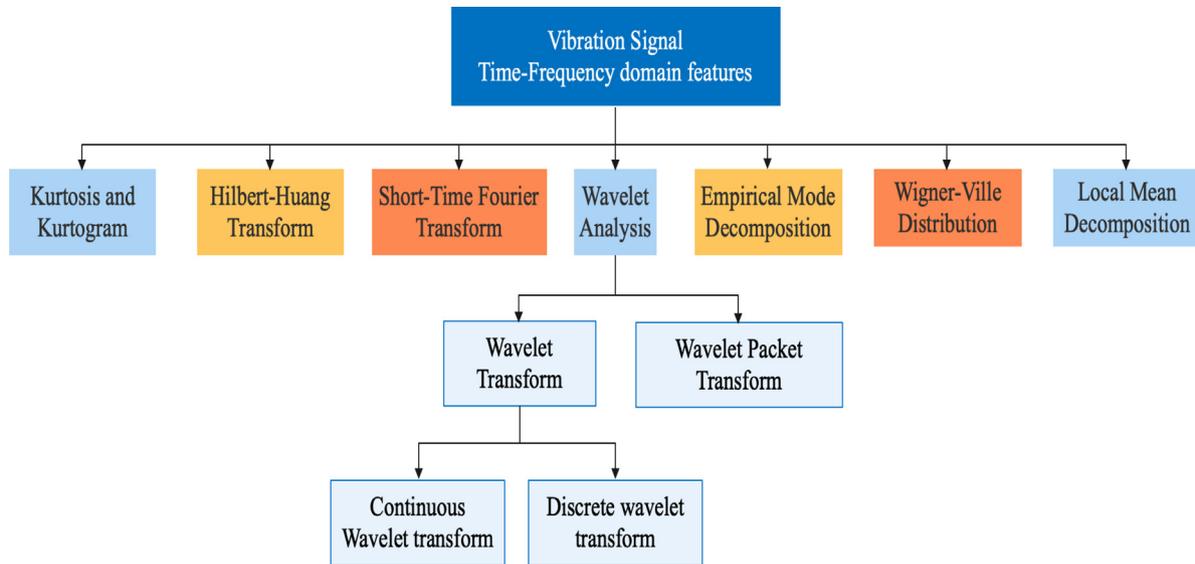


Fig. 14. Overview of time–frequency domain feature extraction methods.

**Table 11**  
Time–frequency domain features along with their definition and formula.

Feature	Property	Formula	Note
Short-Time Fourier Transform (STFT)	Instead of computing the DFT of the whole signal, we decompose a signal into shorter segments of equal length	$STFT_{x(t)}(t, \omega) = \int_{-\infty}^{\infty} x(t)w(t - \tau)\exp(-j\omega\tau)d\tau$	$\tau$ = time variable $w(\tau)$ = window function
Continuous Wavelet Transform	Extension of the Fourier transform maps the original signal from the time domain to the time–frequency domain.	$W_{x(t)}(s, \tau) = \frac{1}{\sqrt{s}} \int x(t)\varphi^*(\frac{t-\tau}{s})dt$	$\varphi^*$ is the complex conjugate of $\varphi(t)$
Discrete Wavelet Transform	Used for the computerized implementation and analysis process of wavelet transforms.	$W_{x(t)}(s, \tau) = \frac{1}{\sqrt{2^j}} \int x(t)\varphi^*(\frac{t-k2^j}{2^j})dt$	$J$ and $k$ are integers
Wavelet Packet Transform	DWT is further decomposed into an approximation signal and a detail signal	$d_{j+1,2n} = \sum_m h(m - 2k)d_{j,n}$	$m$ is no. of coefficients and $d_{j,n}, d_{j+1,2n}$ and $d_{j+1,2n+1}$ are wavelet coefficients at sub-bands $n, 2n, 2n + 1$ resp.
Empirical Mode Decomposition	Nonlinear and adaptive data analysis technique that decomposes the time domain signal $x(t)$ into different scales or Intrinsic mode functions (IMF)	$x(t) = \sum_{j=1}^n c_j + r_n$	$c_j$ is $j$ th IMF and $r_n$ is residual of data $x(t)$ after extraction of $n$ IMFs.
Local Mean Decomposition	Decomposes a complicated signal into a set of product functions (PFs), each of which is the product of an envelope signal and a purely frequency modulated signal.	$x(t) = \sum_{i=1}^m PF_i(t) + u_m(t)$	$m$ is the number of PFs.
Frequency Domain Kurtosis	The ratio of the expected value of the fourth-order central moment of STFT to the expected value of the square of the second-order central moment of STFT	$x_{FDK}(f) = \frac{E\{ x(q, f_p)^4\}}{E\{ x(q, f)^2\}^2}$	$x(q, f) = \sqrt{\frac{h}{m}} \sum_{i=0}^{m-1} w_i x(i, q) \exp(-j f p i)$ where $h$ = interval between successive observations of the process; $w_i = 1$ ; $f = 2\pi/m$ ; $q = 1, 2, \dots, m$ ; $p = 0, 1, 2, \dots, m$ ; $j = \sqrt{-1}$ ; $x(i, q)$ is $i/p$ signal

has its advantage and disadvantage. The choice of fusion method is determined by the application of the user and types of sensors. In the data-level fusion approach, data from commensurate sensors are fused directly. The fused data is then subjected to feature extraction, followed by a pattern recognition method for classification. The models for data fusion include a weighted average method, Kalman filter method, mathematical statistics method, etc. At this level, fused data is more accurate and trustworthy than data obtained from a single sensor. The sensors employed at this level, however, must be comparable. That is, the measurement must be the same or have physical qualities or occurrences that are identical. The weighted value of multi-sensor signals is difficult to establish when using the most prevalent data-level fusion approach, such as weighted fusion. As a result, data-level

applications are constrained in the real world. Data-level information fusion is as shown in Fig. 15 (Jing et al., 2017; Tong et al., 2020a).

In the feature-level fusion, each sensor is used to collect a kind of signal. Feature extraction is subsequently applied to obtain a feature vector. All features are combined to identify the best subset of features, then input into a classifier or decision-level fusion. All non-commensurate sensor features are merged to form a larger single feature set, subsequently employed in a specific classification model. Here, heterogeneous sensors are allowed, and information compression is still superior. As a result, feature-level applications are versatile and widely used. The integration of feature-level algorithms mainly includes the Kalman filter method, fuzzy inference method, neural network method, etc. Decision-level fusion is a type of high-level fusion

**Table 12**  
Literature analysis related to features studied.

PAPER	Time domain features											Frequency domain features					Time-frequency Domain				
	Mean	RMS	Variance	Peak	Kurtosis	Peak to peak	Skewness	Shape factor	Crest Factor	Impulse factor	Clearance factor	Standard Deviation	RMS Variance frequency	Root Variance frequency	Frequency centre	Mean square frequency	Spectral Skewness	Spectral Kurtosis	Wavelet Energy	Wavelet Packet Decomposition	
Chen and Li (2017)	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙	⊙							
Shao et al. (2017)	⊙	⊙			⊙		⊙	⊙	⊙	⊙											
Jablón et al. (2020)	⊙					⊙						⊙									
Janssens et al. (2016)		⊙			⊙				⊙												
Mey et al. (2020)	⊙				⊙							⊙									
Deng et al. (2017)		⊙		⊙	⊙		⊙							⊙	⊙						
Huang et al. (2020)		⊙			⊙		⊙		⊙			⊙									
Zhao et al. (2019)		⊙	⊙		⊙	⊙	⊙										⊙	⊙	⊙		
Gangsar and Tiwari (2018)																				⊙	
Gruyer et al. (2017)	⊙				⊙		⊙	⊙													

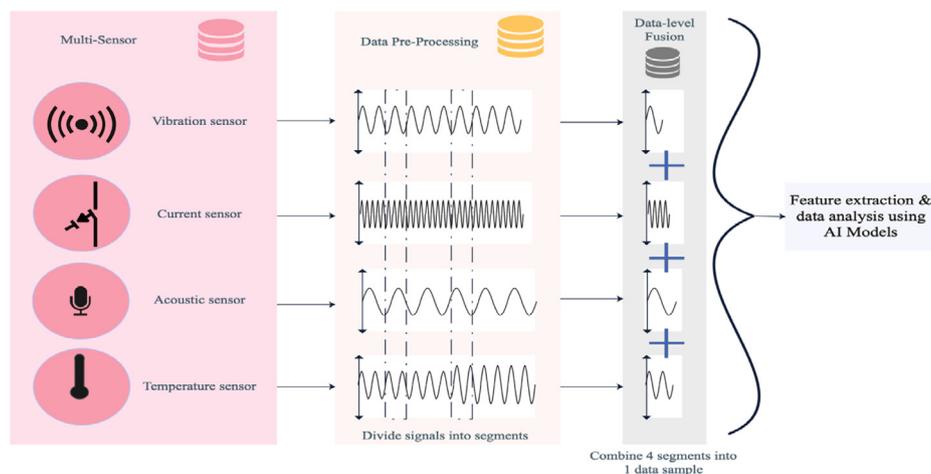


Fig. 15. Data-level Information fusion.

that includes combining the results of several sensors. It stresses the necessity of combining classifiers for a better outcome. The decision level fusion helps minimize the misdiagnosis rates in both false positives and false negatives (Safizadeh and Latifi, 2014). At decision-level fusion, features calculation and pattern recognition processes are applied in sequence for single-source data obtained from each sensor. Decision-level fusion methods are then utilized to fuse the decision vectors. The integration of the decision layer mainly includes Bayesian reasoning, D-S Reasoning, etc. A brief overview of feature fusion and decision level fusion is shown in Fig. 16 (Huang and Liu, 2020; Nacchia et al., 2021).

Based on the type of sensors used, multi-sensor fusion is of three types (Gruyer et al., 2017). Global multi-sensor fusion where homogeneous processing data given by many sensors but represented in a single reference frame is required. The available data is then analyzed as if it

were a single source of information. Second is local/global multi-sensor fusion, where data acquired from different heterogeneous sources is processed. Each sensor’s data will be handled individually in this scenario, and the resulting output information will be homogeneous. This information homogeneity may then be used to execute a global fusion step. Last is the hybrid multi-sensor fusion, which comprises both global multi-sensor fusion and global-local multi-sensor fusion. This design prioritizes highly reliable sensors by providing a local treatment to their data to reduce the impact of less capable sensors. In addition, this design allows for the collection of all homogeneous sensor data to improve output accuracy.

### 3.5.1. Challenges in multi-sensor data fusion:

There are a variety of factors that make data fusion difficult, stated as follows:

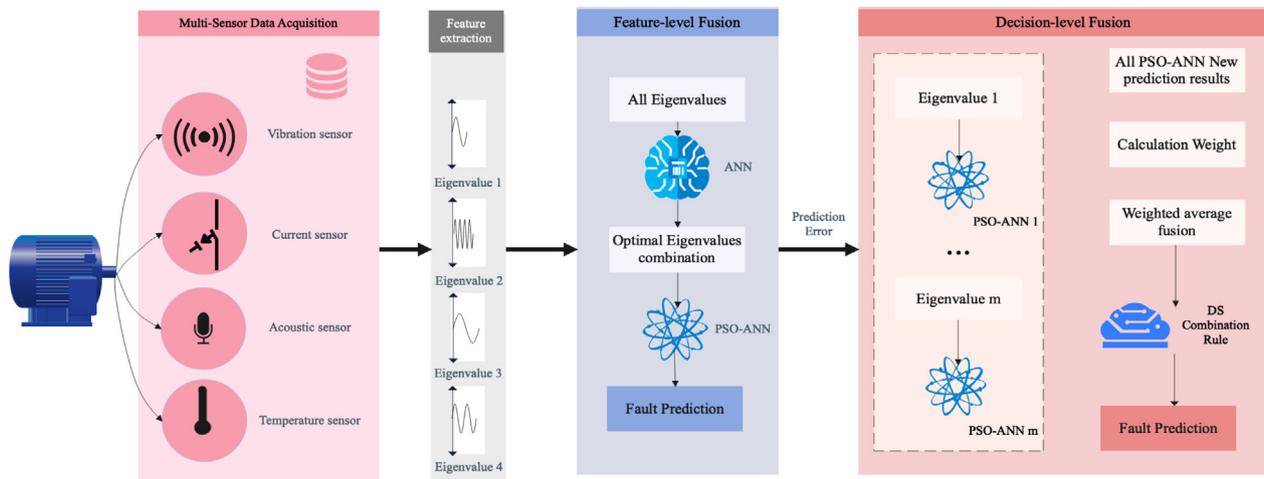


Fig. 16. Information fusion at feature-level and decision-level.

- The bulk of difficulties stem from the data to be merged, the inaccuracy and diversity of sensor technology, and the application environment (Khaleghi et al., 2013).
- The data collected by sensors is always subject to some degree of imprecision and uncertainty in the readings. Data fusion techniques should be able to convey such flaws (Khalastchi and Kalech, 2018) adequately.
- Fusion systems should also handle homogeneous and heterogeneous data as the data can be from a similar type of multiple sensors or multiple types of multiple sensors (Montero Jimenez et al., 2020).
- Measurements acquired throughout the monitoring process in multi-sensor fall detection are generally unrelated and come from diverse sources. Not only should this data be combined in the most efficient way possible, but they should also be examined for common patterns and commonalities (Koshmak et al., 2016).
- Various data sections may travel different paths before reaching the fusion center in distributed fusion setups, resulting in data arriving out of order. To minimize performance deterioration, this issue must be managed appropriately, especially in real-time applications.
- Multi-sensor fusion, as previously said, aids in fault diagnostic reliability. Simultaneously, more sensor devices might considerably raise the monitoring framework's final cost. One should also consider the data acquisition system, which may be costly due to multiple sensors.
- Finally, it is also essential to decide the way of analysis: edge computing or cloud computing. Cloud computing is again very complex due to large data over the cloud (Jagatheesaperumal et al., 2021).

### 3.6. RQ6. How to implement AI models for multi-fault detection?

Artificial Intelligence (AI) has become a widely used technique for data-driven fault diagnosis (Ding et al., 2020). The three primary duties of fault diagnosis are determining if the equipment is normal or not, locating the incipient failure and its cause, and forecasting the fault development trend. Artificial intelligence (AI) has garnered much interest from researchers to accomplish these three objectives, and it shows promise in rotating machinery defect identification applications (Liu et al., 2018). Because of their resilience and adaptability, AI algorithms for fault diagnostics in rotating machinery have grown widespread.

AI-based methods are classified into two categories, considering the profundity of model structures, i.e., Machine learning (ML) and Deep learning (DL). Machine learning is a technique for processing data, learning from it, and making decisions based on what has

been learned (Nguyen et al., 2019). Deep learning creates an “artificial neural network” that can learn and make smart decisions by stacking algorithms. In other words, Deep learning can be called a subset of machine learning. Next, based on supervision, Machine learning is classified as supervised and unsupervised learning. Algorithms like K-Means (Diez-Olivan et al., 2017; Kamat et al., 2021), Neural network (NN), etc., are examples of unsupervised ML. Supervised machine learning (Çinar et al., 2020) is of two types based on the tasks to be accomplished. They are classification and Regression. Classification algorithms are used to classify multiple faults in machinery. Regression algorithms assist us in predicting the upcoming faults based on experience or, in other words, the Remaining Useful Life (RUL) (Kumar et al., 2022a) of machinery. K-Nearest Neighbor (KNN) (Baraldi et al., 2016), Back Propagation (BP), Support Vector Machine (SVM) (Liu et al., 2018; Hui et al., 2017; Wang et al., 2014) are examples of classification algorithms. Random forest (RF), Artificial Neural network (ANN) (Luwei et al., 2018), Linear regression (LR), Gaussian Process Regression (GPR), Support vector regression (SVR) are some algorithms for regression (Akhil et al., 2020). Deep learning can be a comprehensive and effective response to most questions related to machine health monitoring systems (MHMS) for addressing big data and learning multi-scale/multi-facet/stratified representation. There are different variants of Deep learning algorithms such as Recurrent Neural Networks (RNN) (Zhao et al., 2019), Auto-encoders (AE) (Chen and Li, 2017), Convolutional Neural Networks (CNN) (Zhao et al., 2019; Kumar et al., 2022b), Deep Belief Network (DBN) (Chen and Li, 2017; Wang et al., 2014), and Deep Boltzmann Machines (DBM) (Zhao et al., 2019). In recent years, researchers have successfully implemented these models in the field of Predictive maintenance. Sometimes hybrid of these methods, that is, multiple data-driven algorithms or a combination of data-driven and physics-based algorithms, are used, which are more effective.

A representation of different algorithms used for fault diagnosis and the types of faults diagnosed using both data-driven and hybrid approaches are depicted in Tables 13 and 14. Table 13 analyses the data-driven approaches currently employed by researchers for fault diagnosis in industrial rotating machines, as discussed earlier. Table 14 is the analysis of hybrid approaches using knowledge-based, physics-based, and data-driven approaches used by the researchers. For example, Satish and Sarma (2005) presented a hybrid knowledge-based and data-driven approach for fault diagnosis using Fuzzy logic and a Neural network to predict RUL. Swanson (2001) proposed a hybrid of knowledge-based and physics-based approaches using Fuzzy logic and Kalman filter to predict damage in aircraft actuator faults. Zhang et al. (2002) proposed a similar hybrid of fuzzy logic and wavelet neural networks to calculate RUL. Liu et al. (2012) proposed a hybrid,

**Table 13**  
Contribution of data-driven approach for fault diagnosis of rotating machine.

Algorithm	Algorithm type	Definition	Diagnosis application	Accuracy	Advantages	Limitations	Ref.
Deep belief network (DBN)	Deep Learning	The DBN is a deep architecture with multiple hidden layers that can learn hierarchical representations automatically in an unsupervised way and perform classification at the same time.	Fault in Induction motor, Bearing faults, etc.	99.9% (Tao et al., 2016) 97.82% (Chen and Li, 2017)	Efficient usage of hidden layers processes unlabeled data effectively, and the problem of overfitting and underfitting may also be avoided	Increasing run time complexity.	Shao et al. (2017) Tao et al. (2016) Chen and Li (2017)
Auto Encoder (AE)	Deep Learning	An AE is an unsupervised neural network with three layers, which could take an input vector to form a high-level concept in the next layer through a nonlinear mapping.	Bearing faults	100% (Shi et al., 2020) 98.3% (Mao et al., 2021)	Can combine multi-sensor data, prior knowledge not essential	Wide range of data needed, unable to identify relevant information	Chen and Li (2017) Shi et al. (2020)
Deep Neural Network (DNN)	Deep Learning	DNNs have deep architectures containing multiple hidden layers, and each hidden layer conducts a non-linear transformation from the previous layer to the next one.	Fault in Bearings and gearbox	99.06% (Akhtari et al., 2019) 100% (Sohaib et al., 2017)	automatically deduced and optimally tuned for the desired outcome, robust, flexible	Needs wide range of data for training, overfitting issue	Jia et al. (2016) Akhtari et al. (2019) Sohaib et al. (2017)
Convolutional Neural Network (CNN)	Deep Learning	A CNN is a Deep Learning algorithm that can take in an input image, assign importance (weights) to various aspects/objects in the image and be able to differentiate one from other	Fault in bearings, unbalance, motor faults, pump faults	93.54% (Wang et al., 2019) 90.24% (He et al., 2021a)	Needs less storage, is less complex compared to ANN, better autodetection	Needs wide range of data for training, overfitting issue, the high computational cost	Janssens et al. (2016) Wang et al. (2019) He et al. (2021a)
Artificial Neural Network (ANN)	Deep Learning	An ANN is based on a collection of connected units or nodes called artificial neurons, which loosely model the neurons in a biological brain.	Fault in bearing, misalignment, rotor bar faults	94% (Luwei et al., 2018) 97.89% (Huang and Liu, 2020)	Good adaptability, high tolerance for defects, better prediction, and classification.	Needs wide range of training data, overfitting issue, std. network structure not defined	Liu et al. (2018) Luwei et al. (2018) Huang and Liu (2020)
RNN/LSTM	Deep Learning	A recurrent neural network (RNN) is a class of ANN where connections between nodes form a directed graph along a temporal sequence.	Gearbox fault, tool fault, RUL, bearing fault	RNN: 94.6% LSTM: 99.2% (Udmale and Singh, 2019)	RNN: easy to process for long i/p, weight can be shared across time-steps. LSTM: better for time-series data, can deal with vanishing gradient problem.	RNN: more computation time, hard for training, gradient vanishing problem. LSTM: Requires more time and resources for training.	Zhao et al. (2019) Udmaale and Singh (2019)
KNN	Machine Learning	KNN is an algorithm where k denotes the number of nearest neighbors used to predict the class of a sample.	Faults like Unbalance, bearing faults	98.61% (Xia et al., 2018)	No training period, simple, new data can be added easily	Not suitable for large dataset, sensitive to noisy data, need feature scaling	Jablon et al. (2020) Xia et al. (2018)

(continued on next page)

Table 13 (continued).

Algorithm	Algorithm type	Definition	Diagnosis application	Accuracy	Advantages	Limitations	Ref.
SVM	Machine Learning	It provides a boundary in the input feature space by considering patterns and relationships on the inputs. Boundaries are then used to create a decision rule used for classification	Faults like Unbalance, bearing, misalignment, wind turbine	98.83% (Xia et al., 2018) 80% (Janssens et al., 2016)	Better performance for adequate sample size, semi and unstructured data, high dimensional data	Depends on the penalty parameter which is selected by the trial and error method, a standard kernel function is not defined	Jablon et al. (2020) Xia et al. (2018) Janssens et al. (2016)
Random forest	Machine Learning	RF is an ensemble learning method for classification, a regression that operates by constructing a multitude of <b>decision</b> trees at training time and outputting the class that is the mode of the classes (classification) or mean/average prediction (regression) of the individual trees	Faults like unbalance in the rotor, bearing, impeller, blower	87.2% (Janssens et al., 2016)	Reduces overfitting, flexible, it automates missing value present in data	Need high computational power, time for training suffers interpretability and fails to determine the significance of each variable	Raina et al. (2007) Janssens et al. (2016)
Extreme Learning Machine (ELM)	Machine Learning	ELM is a feedforward neural network for classification, clustering, regression, with a single layer or multiple layers of the hidden node	Fault in bearings, gearbox	98.84% (Udmale and Singh, 2019) 95.40% (Pan et al., 2019)	Short training time, simple to use	Overfitting	Udmale and Singh (2019) Pan et al. (2019)

**Table 14**  
Contribution of hybrid PdM approach for fault diagnosis of rotating machine.

Algorithm	Hybrid PdM approach	Definition	Diagnosis application	Ref.
Fuzzy logic + NN	Knowledge-based + Data-driven	Fuzzy logic is an approach to variable processing that allows for multiple values to be processed through the same variable.	Gearbox faults, RUL prediction	Satish and Sarma (2005)
Fuzzy logic + Wavelet neural network	Knowledge-based + Data-driven	Wavelet networks are a new class of networks that combine the classic sigmoid neural networks (NNs) and the wavelet analysis (WA).	RUL prediction of bearing	Zhang et al. (2002)
EMD + PSO + SVM	Hybrid of Physics-based model	Empirical Mode Decomposition performs operations that partition a series into 'modes' (IMFs; Intrinsic Mode Functions) without leaving the time domain. Particle Swarm Optimization is a computational method that optimizes a problem by iteratively improving a candidate solution concerning a given measure of quality.	Pump fault, RUL	He et al. (2012)
Fuzzy logic + Focused TLFN	Knowledge-based + Data-driven	In the Feedforward Neural network, the information moves in only one direction from the input nodes, through the hidden nodes (if any) and output nodes. Thus, there are no cycles or loops in the network.	Cutting tool monitoring, RUL	Chinnam and Baruah (2004)
Fuzzy logic + Kalman filter	Knowledge-based + Data-driven	Kalman filtering is an algorithm that provides estimates of some unknown variables given the measurements observed over time.	Actuator fault, RUL	Swanson (2001)
SVR + HMM	Hybrid data-driven approach	The Support Vector Regression uses the same principles as SVM for classification. However, it allows us to define how much error is acceptable in our model and find an appropriate line to fit the data.	Bearing RUL	Liu et al. (2012)
MLP + RBF + KF	Data-driven + Physics-based approach	Multi-layer Perception is a class of Feedforward NN which refers to networks composed of multiple layers of perceptrons. A radial basis function is a real-valued function whose value depends only on the distance between the input and some fixed point, either the origin or another fixed point called the center.	RUL prediction	Peel (2008)
GPR + KF/PF	Data-driven + Physics-based approach	Gaussian process regression is nonparametric, Bayesian approach to regression that is making waves in machine learning. Particle filters or Sequential Monte Carlo (SMC) methods are a set of Monte Carlo algorithms used to solve filtering problems arising in signal processing and Bayesian statistical interference.	RUL prediction	Celaya et al. (2014)
SK + ELM	Data-driven + Physics-based approach	The spectral kurtosis (SK) is a statistical tool that can indicate the presence of series of transients and their locations in the frequency domain.	Bearing faults	Udmale and Singh (2019)

multiple data-driven approach using HMM and SVR to predict the RUL of bearings again. Celaya et al. (2014) proposed a hybrid data-driven and physics-based approach using GPR and KF/PF to predict the RUL of power devices. The experimental results from all these studies show that the hybrid approach yields better results than other independent approaches. Hybrid approaches boost the advantages and conceal the disadvantages of different independent approaches to yield a better diagnosis. However, there are a few challenges while employing the hybrid approach. This includes which kind of approach is appropriate, availability of data and other resources, proper fusion technique of the data as the data can be of various types, with different sampling rates, etc.

### 3.6.1. Machine learning styles

Machine learning emphasizes “learning”, because of which there are different Machine learning techniques available. It is vital to know what type of Machine learning can be used in the fault diagnosis of rotating machines. These techniques are broadly classified as learning problems, hybrid-learning problems, statistical inference, learning techniques, and other important learning approaches (Brownlee, 2019; Sah, 2020). First are the three main learning problems in machine learning: supervised, unsupervised, and reinforcement learning (Nacchia et al., 2021). The term “supervised learning” refers to an issue in which a

model is used to learn a mapping between input instances and the target variable. In this case, class labels should be available in advance. Also, the class labels are extremely biased to normal class, whereas the anomalies appear rarely. Unsupervised learning refers to a set of issues in which a model describes or derives relationships from data. Here, the models treat instances that fit least to the majority as anomalies. Also, the model learns from partially labeled normal data and scale anomaly to the difference between an unseen pattern and the learned normal pattern. The difficulty here is that most of the machinery data is sequential and collected over a longer period. However, prediction over a longer sequence may be challenging as the length of the input sequence can vary. Reinforcement learning (Koprinkova-Hristova, 2013) is a type of online learning that simultaneously combines the learning and action phases and has a self-optimizing characteristic. The distinction between unsupervised and supervised learning is hazy, and several hybrid techniques include elements from both fields like semi-supervised, self-supervised, multi-instance learning, etc.

Semi-supervised learning (Du Toit, 2014) employs unlabeled instances to aid in learning the probability distribution over the input space. It also simultaneously optimizes the prediction over labeled and unlabeled examples. Self-supervised learning (Wu et al., 2021) is a representation learning approach in which unlabeled data is used to construct a supervised task. Self-supervised learning is used to lower the

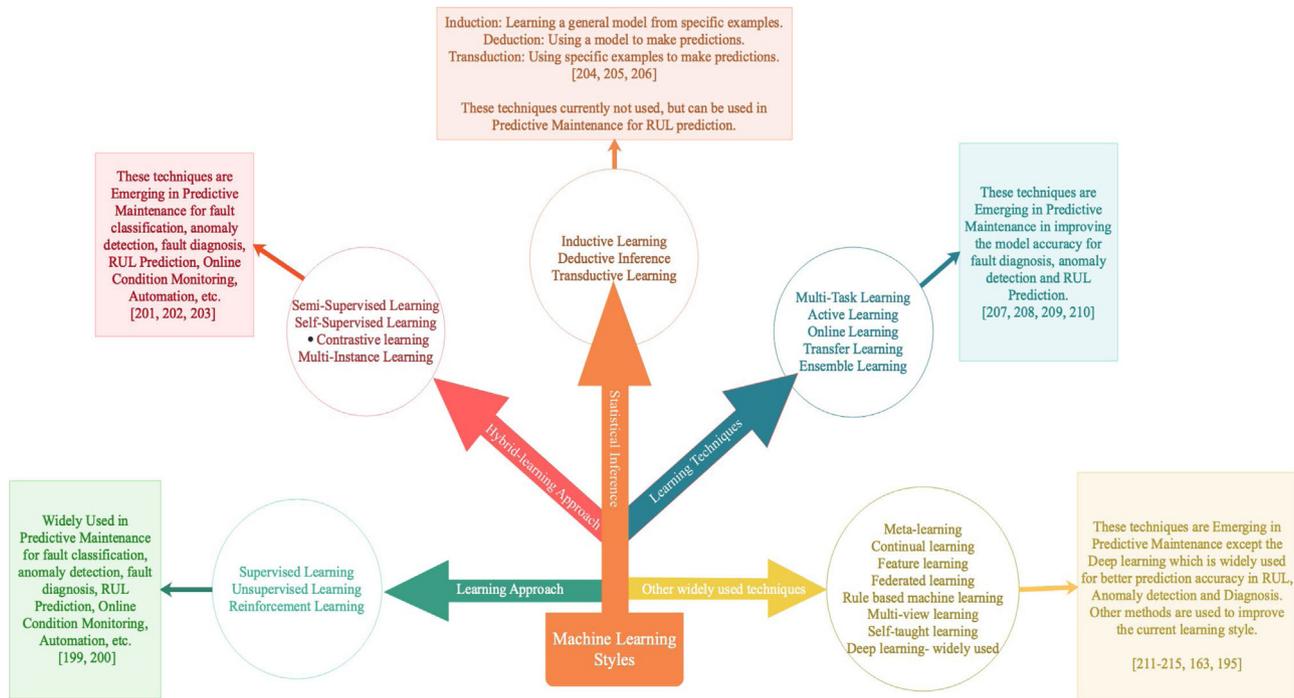


Fig. 17. Overview of various machine learning styles.

expense of data labeling and use the unlabeled data pool. Contrastive learning (Rombach et al., 2021), a type of self-supervised learning, identifies comparable and dissimilar objects for an ML model in a different way. The fundamental goal of contrastive learning is to develop representations that keep comparable samples near together while a large distance separates different samples. Contrastive learning is one of the most powerful techniques in self-supervised learning when working with unlabeled data. Multi-instance learning is a supervised learning problem in which individual instances are not labeled, but bags or groups of samples are.

The process of arriving at a conclusion or judgment is known as inference. Both fitting a model and making a prediction are examples of inference in machine learning. It is the next category of learning, including techniques such as Inductive Learning, Deductive Inference, Transductive Learning, etc. Inductive learning (Michalski, 1983) entails determining the result based on evidence. The deduction, also known as deductive inference (Sammur and Webb, 2010), uses general rules to arrive at specific conclusions. In the realm of statistical learning theory, the term “transduction” or “transductive learning” (Brazinskas et al., 2021) refers to predicting particular cases given specific examples from a domain.

There are several strategies classified as learning techniques. It encompasses multi-tasking, active learning, online learning, transfer learning, and ensemble learning. Multi-task learning (Allah Bukhsh et al., 2020) is a form of supervised learning in which a model is fitted to a single dataset to solve numerous related tasks. Active learning (Tham and Rajagopalan, 2020) is an approach in which the model may ask a human user operator question throughout the learning process to clarify ambiguity. Online learning entails using the data at hand and updating the model immediately before making a prediction or after the final observation. Transfer learning (Han et al., 2021) is a form of learning in which a model is initially trained on one task and then utilized as the starting point for another activity. Ensemble learning (Zhang et al., 2015) is a technique in which two or more models are fitted to the same data, and their predictions are pooled.

Apart from these, there are many other techniques for machine learning such as meta-learning, continual learning, feature learning, federated learning, rule-based machine learning, multi-view learning,

self-taught learning, deep learning, and many more. Learning algorithms that learn from other learning algorithms are called meta-learning (Feng et al., 2021) in machine learning. A model’s capacity to learn continuously from a data stream is known as continual learning (Parisi et al., 2019). In reality, this means enabling a model to learn and adjust autonomously in production as new data arrives. Feature learning (Nithin and Sivakumar, 2015), also known as representation learning, is a collection of machine learning algorithms that allow a system to automatically find the representations needed for feature detection or classification from raw data. It eliminates the need for human feature engineering by allowing a machine to learn and use features to fulfill a given activity. Federated learning (Mohr et al., 2020) is a technique for training machine learning algorithms across numerous edge devices without exchanging training data. Federated learning, as a result, provides a novel learning paradigm in which statistical techniques are taught at the network’s edge. The rule-based machine learning approach of association rule learning identifies interesting relationships between variables in big databases. Multiview learning (Huang and Liu, 2020), also known as data fusion or data integration from various feature sets, incorporating several perspectives to increase generalization performance. Self-taught learning (Raina et al., 2007) is a new paradigm in machine learning. It uses labeled data belonging to the desired classes and unlabeled data from other, somehow similar classes. Many machine learning researchers have endorsed newer advances such as Deep Learning (DL) (Tang et al., 2020). Due to its improved capacity to describe system complexity, DL has emerged as a viable computational tool for dynamic system prediction, overcoming the drawbacks of conventional techniques. In deep architecture, it is a machine learning approach that learns many levels of representations. Out of all the learning techniques, Supervised learning for classification (forecasts if the following n-steps have a chance of failure) and regression (to predict Remaining Useful Life), unsupervised learning (for anomaly detection), reinforcement learning, hybrid learning methods, transfer learning, ensemble learning, deep learning, meta-learning, ensemble learning, etc. are widely used. Fig. 17 summarizes all the machine learning techniques discussed above.

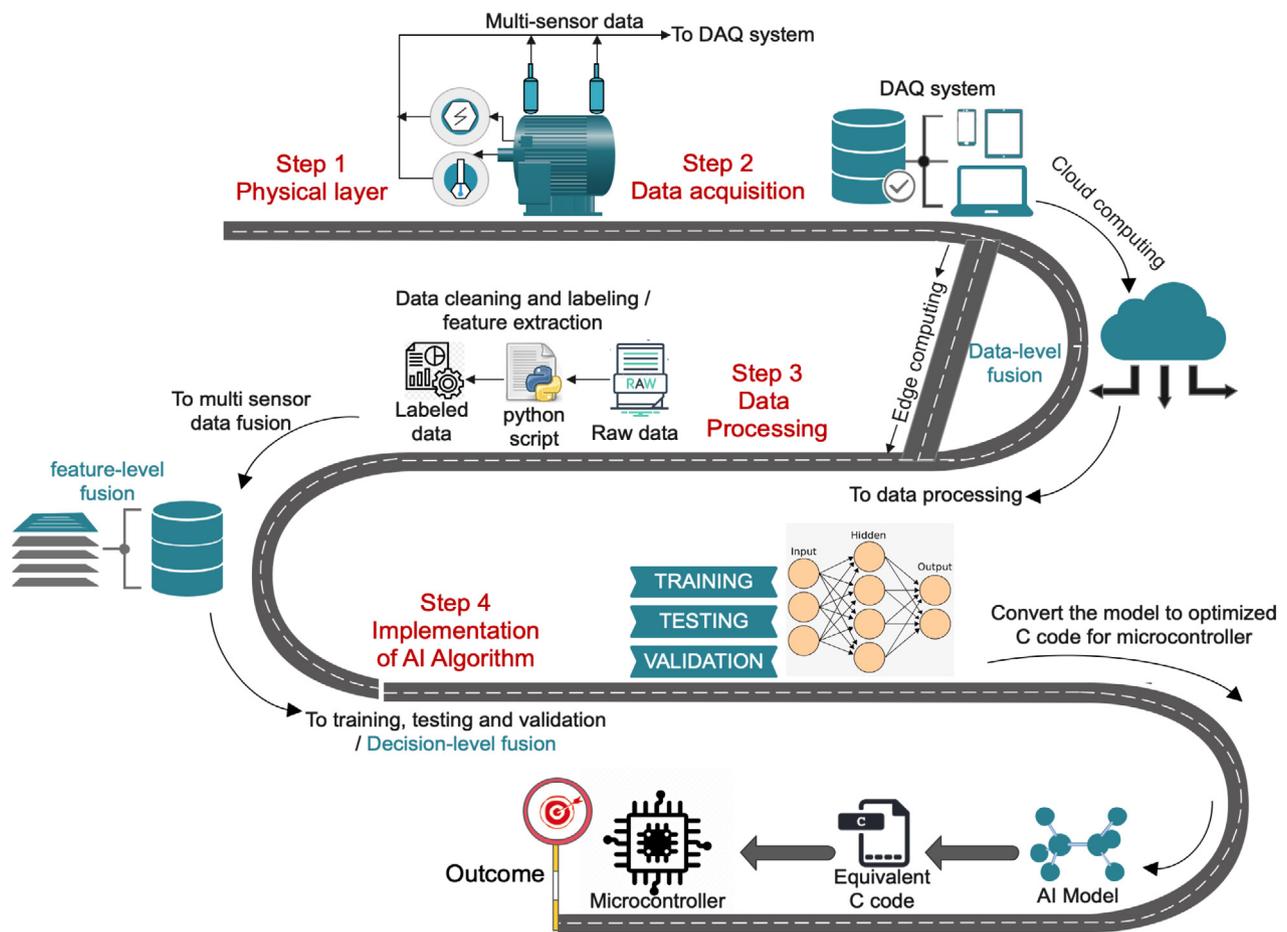


Fig. 18. Implementation stack of AI for multi-fault diagnosis of rotating machines.

### 3.6.2. Steps to implement AI model in fault diagnosis of rotating machines.

The implementation stack of AI for multiple fault diagnosis is depicted in Fig. 18. The figure is divided into several layers connected through a single directional road map. Each layer reveals a specific task accomplished via a particular set of either hardware or software or protocols or data stores. The first and the primary layer is the physical layer that includes the machine under test, the different sensors, the data communication medium, and the data acquisition system. Before moving ahead, it is essential to decide whether cloud computing or edge computing will be employed in fault diagnosis. Data pre-processing is the next important task that involves data storage, feature extraction, and data fusion. The next step is implementing the data analysis using ML/DL algorithms to achieve an accurate diagnosis. It includes training, testing, and validation of the algorithm and the results obtained. Once the diagnosis results are obtained, the final step is to convert the model to optimized C code to be implemented on the microcontroller. The advantages of using microcontrollers are: they consume low energy, are cheap, they are flexible, and most importantly, they have high security. Some widely used microcontrollers include Coral Dev Board, NVIDIA® Jetson Nano™ Developer Kit, Raspberry Pi 4 computer model B, etc.

## 4. Discussion

With Artificial Intelligence (AI) advancement, a data-driven approach for predictive maintenance is taking a new flight towards smart manufacturing. This approach for multiple fault diagnosis in Industrial Rotating Machines is a never-ending research field. The literature review has developed new insight into the various aspects that a researcher should know before taking a step in this field. In this regard, let us discuss the survey outcome in the following subsection.

### 4.1. Survey outcome

Let us analyze the survey outcome concerning the various aspects studied in the literature through Table 15. Finally, Fig. 19 gives the summary of the literature review.

### 4.2. Challenges and limitations in multi-fault diagnosis

The challenges and limitations of multi-fault diagnosis are discussed in this paper that may aid in further research. Table 16 gives a systematic overview of the challenges and limitations.

### 4.3. Advancements in data-driven multi-fault diagnosis in the context of Industry 4.0

Artificial intelligence progress is genuine and occurring with the technology finding extensive use in nearly every industry. In such industries, Predictive maintenance, which is a method of gathering, analyzing, and utilizing data from different industrial sources such as machines, sensors, and switches, uses intelligent algorithms to analyze data to predict equipment failure before it occurs. Companies are already using continuous monitoring technologies like the Internet of Things (IoT). However, the key to increasing company efficiency is going beyond simply monitoring the output of multiple technologies and using powerful techniques in machine learning to act on real-time insights and improve upon significant issues faced by current techniques. Predictive maintenance is at the heart of industrial innovation, and it entails rethinking and optimizing the whole maintenance approach from top to bottom. AI-led approaches have addressed some open issues in the multi-fault diagnosis of rotating machines. These approaches

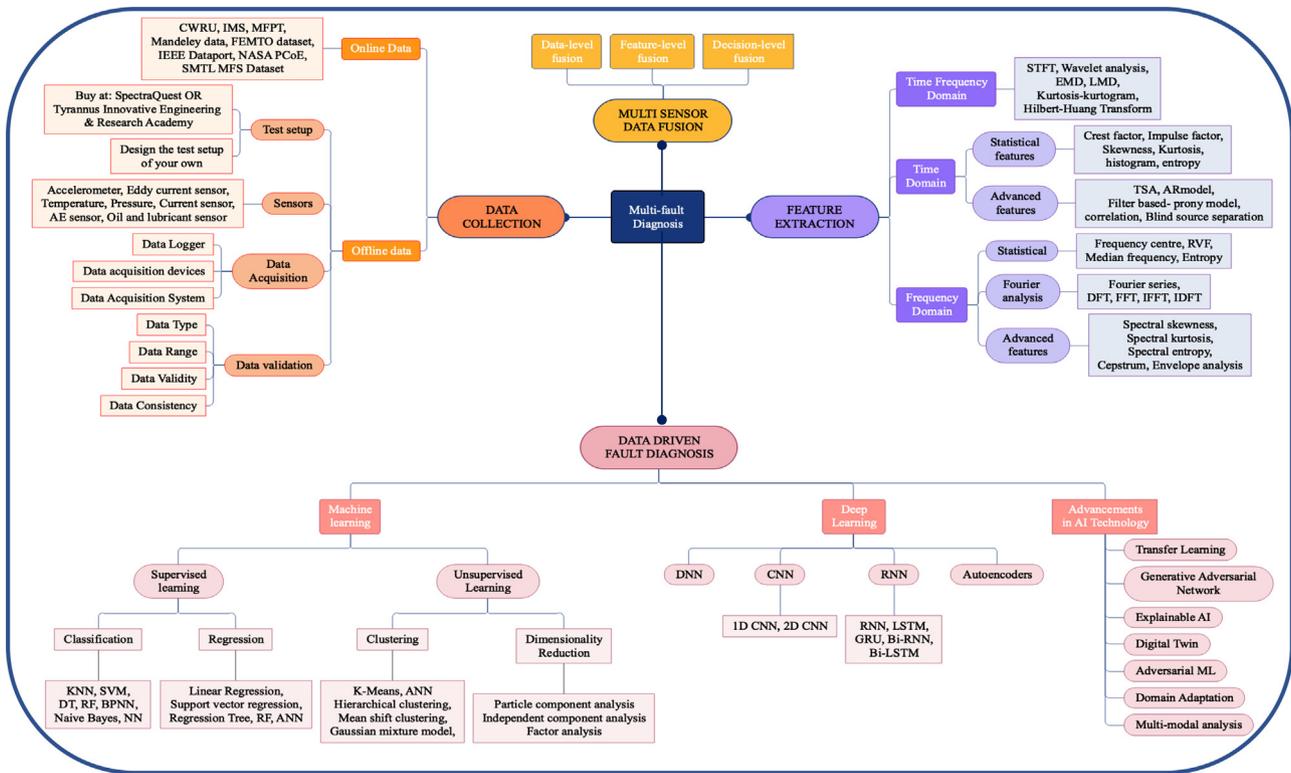


Fig. 19. Complete summary of literature review.

Table 15  
Survey outcome discussion.

Survey topic	Outcome
Maintenance strategy	Maximizing equipment reliability and facility performance while balancing the related resources used and, consequently, the cost is the goal of a good maintenance strategy. In this regard, there is a need to blend all the maintenance philosophies to provide the best strategy that would increase the RUL of the machine, Predictive maintenance being the core of all.
Data source	There are online datasets available. However, the best choice regarding validity and accuracy is to yield an accurate diagnosis, design a test setup, and collect data manually to train the AI models.
Sensors	Sensor fusion refers to the capacity to combine data from various sources and sensors to create a single model or representation of the world surrounding the machinery. Because the strengths of the many sensors are balanced, the final model is more accurate.
Data acquisition	There are a variety of data acquisition options available. One must choose a suitable system based on the application and compatibility. It is always better to decide the data acquisition method before the purchase of sensors and other apparatus.
Signal processing	Feature selection is critical in signal processing. For non-stationary signals, which are very common while machinery failure, features from the time–frequency domain need to be used for better results.
AI techniques	Hybrid data-driven approaches boost the advantages and conceal the disadvantages of different independent AI techniques to yield a better diagnosis.

include generative adversarial networks, explainable AI, transfer learning, domain adaption, digital twin, adversarial machine learning, and domain adaptability. Fig. 20 depicts some of these challenges and the solutions given by these approaches.

#### 4.3.1. Generative Adversarial Networks (GAN)

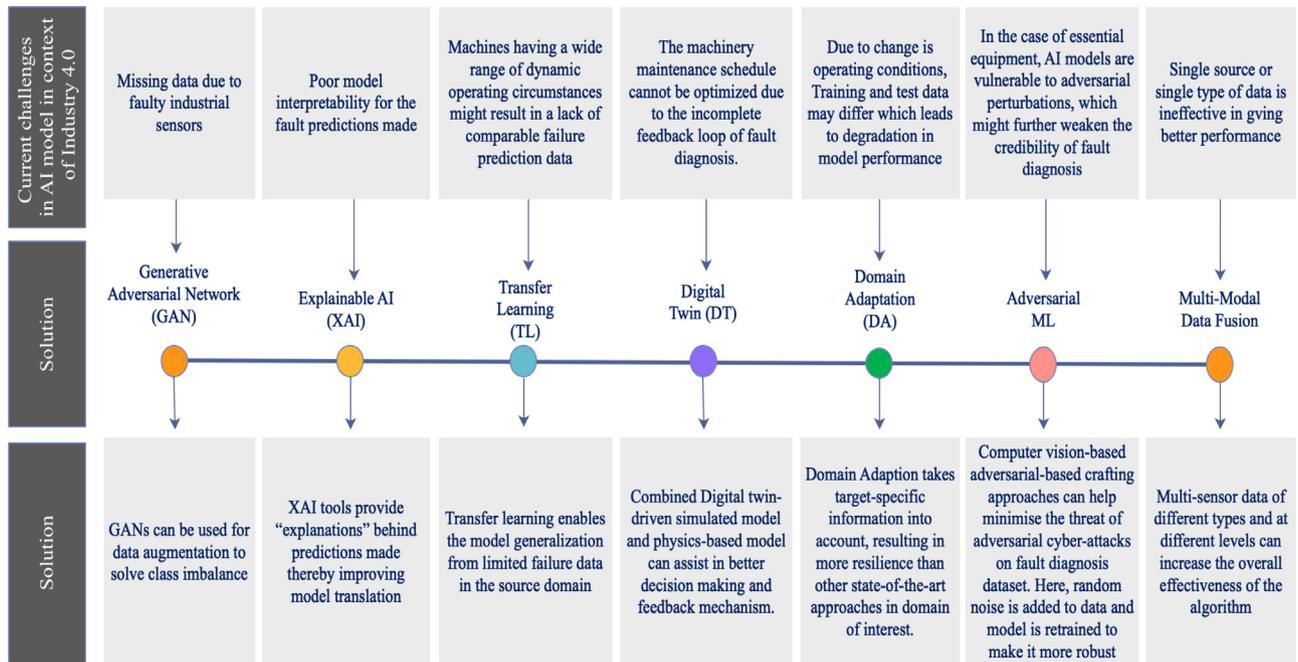
Sensors installed to collect machine condition data might malfunction due to inadequate power supply. The data might differ due to constantly changing conditions in the manufacturing industries, leading to data shortage. The highly unbalanced training data, the extremely high cost of obtaining more failure examples, and the intricacy of the failure patterns can also add to further challenges. GAN starts by using two GAN networks to produce training samples and develop an inference network that may be used to forecast new sample failures. GAN is used to synthesize virtual artificial data, an unsupervised learning approach involving the interaction of two neural networks (Liu et al., 2020b). The GAN is made up of two parts: a generator and a discriminator. The generator’s job is to create synthetic data as close to the actual sample as feasible, while the discriminator’s job is to separate real samples from fake samples as much as possible. The schematic of GAN is as shown in Fig. 21 (Liu et al., 2020b). Mode collapse, Non-conversions, instability, and Evaluation matrix issues are some of the challenges in implementing GANs (Saxena and Cao, 2020). One possible study direction is to investigate how these approaches might be applied to more complicated datasets containing vibration and time-series data (Fink et al., 2020).

#### 4.3.2. Explainable AI (XAI)

As the industries are turning towards automation, users are progressively outsourcing more jobs to computers. Users may find it challenging to grasp such complicated systems since they are generally developed utilizing “black box” Artificial Intelligence (AI). Traditional black-box AI algorithms might be more transparent by offering explanations of the findings or building explainable and interpretable AI solutions for Industry 4.0 applications (Wagle et al., 2021). Future

**Table 16**  
Challenges and limitations of multi-fault diagnosis in industrial rotating machines.

Challenges	Issues	Impact on multi-fault diagnosis
Data related challenges	Data availability	Machines with a wide range of dynamic operating circumstances might lack complete data with a comparable distribution for fault diagnosis.
	Data accessibility	Failure to access high-quality data in a defined format for AI models may harm the models' performance.
	Data quality	Due to a lack of access to high-quality data, firms and governments may be forced to develop subpar AI systems for fault diagnosis systems.
	Data acquisition/transmission	If appropriate and high-speed communication and data acquisition systems are not available, critical information may be truncated.
	Single sensor data	If only one type of data is used to train the AI model, it may not be effective. The diagnosis is incomplete by depending on the single type of data.
	Cost for data collection	Due to the high cost of machinery parts, it is challenging to run the machinery until failure for data collection.
AI model related challenges	Class imbalance	This happens mostly because healthy data is much more than fault data.
	Model interpretability	Inability to understand why a particular diagnosis was given at a specific point in time due to a lack of model interpretability
	Adversarial perturbation	In the case of essential equipment, AI models are vulnerable to adversarial perturbations, which might further weaken the credibility of fault diagnosis
	Inefficiency of the model for similar (not exact) data.	The data is never the same for training and testing due to broad operating conditions and circumstances in an Industrial environment.
Network and security	Cloud computing	Concerns about security, privacy, and real-time performance may arise while using cloud computing. As a result, it is necessary to verify the dispersed resource sharing of critical industrial data.
	Privacy of the data	Designing safe and hack-free durable intelligent diagnosis is a significant problem due to its complexity.



**Fig. 20.** Summary of challenges and the corresponding advancements in AI models.

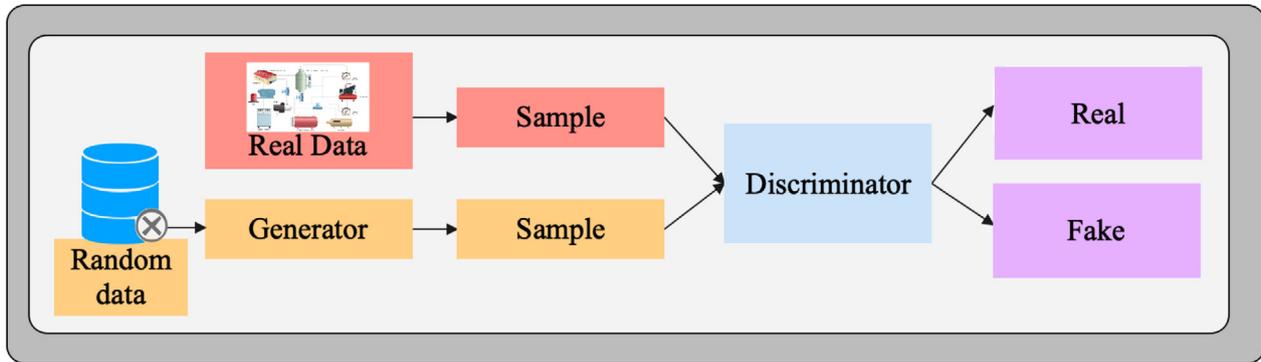


Fig. 21. GAN architecture.

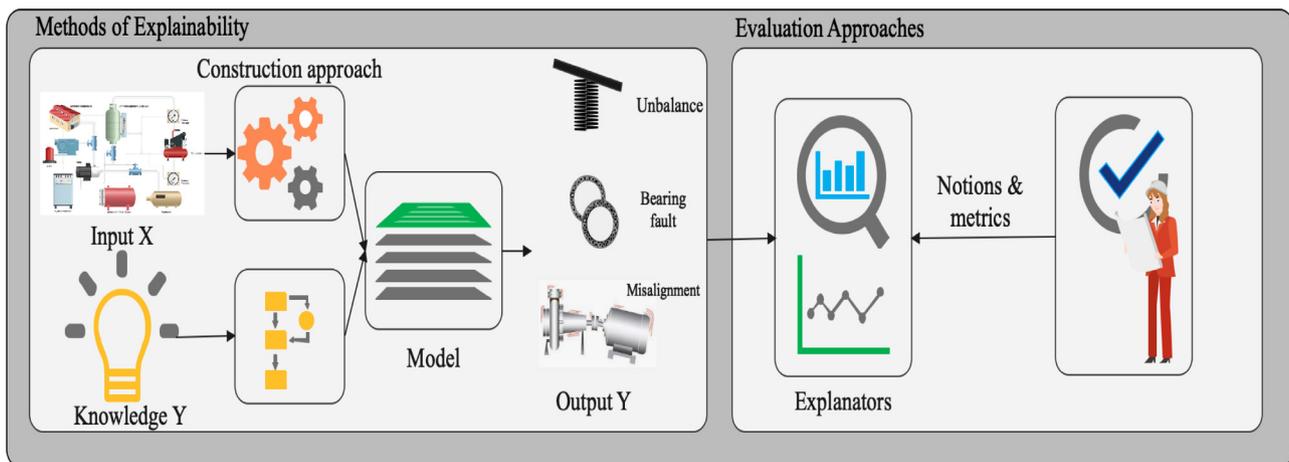


Fig. 22. XAI architecture.

research into Explainable AI (XAI) in predictive maintenance is critical since interpretability and clarity are essential aspects for building credibility and security. Galanti et al. (2020) suggested an explainable AI solution for process monitoring. On real industrial benchmark datasets, the suggested solution is assessed. Rehse et al. (2019) have also examined the challenges and possible applications of explainable AI in Industry 4.0 in great depth. Defining the relevant evaluation mechanisms, procedures, measures, and methods are some of the challenges in Explainable AI. The quality, usefulness, and satisfaction of the explanations, and the influence of explanations on the model's success are all factors to consider when evaluating the XAI (Barredo Arrieta et al., 2020). Fig. 22 (Vilone and Longo, 2020) shows the architecture to implement XAI.

#### 4.3.3. Transfer Learning (TL)

Transfer learning is the concept of breaking out from the isolated learning paradigm and using what has been learned to tackle related problems. Due to constantly changing conditions in manufacturing units, the data is never the same, but it can be similar. Transfer Learning (TL) methods can enhance model accuracy for pre-and post-model deployment in dissimilar data distribution across the source and target domains. Fig. 23 (Xu et al., 2019) is an architecture of Digital Twin assisted transfer Learning. The paper's authors devised a technique known as Digital-twin-assisted Fault Diagnosis using Deep transfer learning (DFDD). In the first phase, the potential problems that are not considered at design time were discovered by front running the ultra-high-fidelity model in the virtual space. In contrast, a Deep Neural

Network (DNN) based diagnosis model was fully trained. In the second phase, the previously trained diagnosis model was migrated from the virtual to physical space using Deep Transfer Learning (DTL) for real-time monitoring and predictive maintenance. Implementing transfer learning for multiple fault diagnosis is currently an emerging research area.

#### 4.3.4. Digital Twin (DT)

The goal of a Digital Twin is to construct a very accurate virtual replica of a physical system or process to mimic system behavior, condition monitoring, unusual pattern identification, system performance reflection, and future trend projection (Kumar et al., 2020). The ability to produce simulated data is one of Digital Twin's features. Infinite cycles of situations must be run in a simulated environment. The simulated data collected may subsequently be utilized to successfully train a naive AI model on the various elements of manufacturing operations. The digital twin's next skill is finding, planning, and testing new features that may be utilized to supplement data operations in a machine learning process. Finally, a digital twin can help with data augmentation for imbalanced datasets. DT is extensively used for predictive maintenance, fault diagnosis, detecting system abnormalities, inferring product quality, real-time system monitoring, and so on (Xu et al., 2019; Luo et al., 2020; Tong et al., 2020b). Fig. 23 (Xu et al., 2019) is an architecture of Digital Twin assisted transfer Learning. However, digital twin challenges are accurately capturing physical properties, project collaboration, automatic real-time updating, conflict detection and resolution, and interaction with digital and physical items. Digital

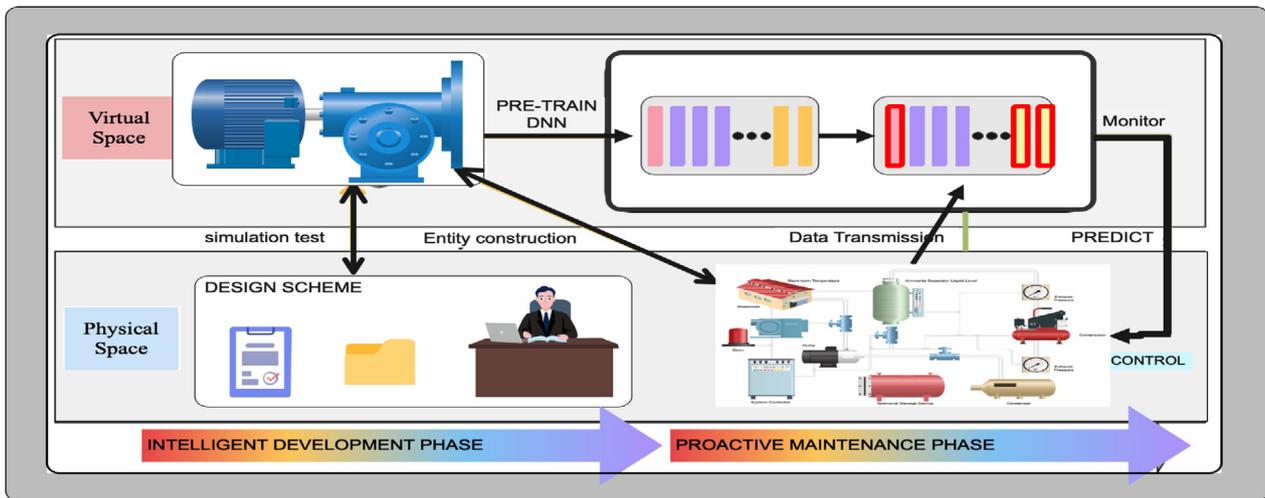


Fig. 23. Digital Twin assisted transfer learning.

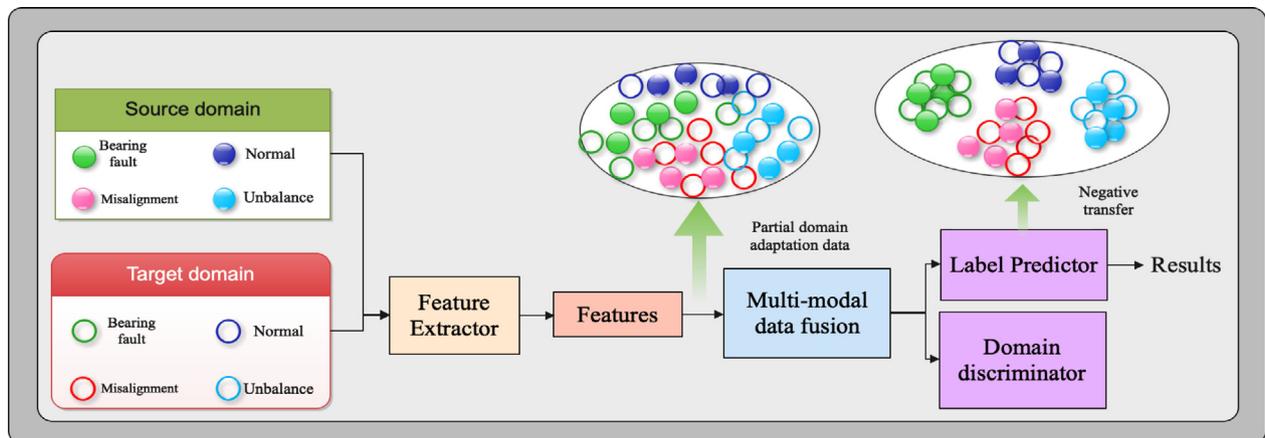


Fig. 24. Adversarial domain adaptation architecture.

Twin enabled fault diagnosis can be implemented, which can help leverage the real-time and wholistic information related to machinery giving feedback between the real and digital world at every stage.

#### 4.3.5. Domain Adaptation (DA)

Fault diagnostic models are created with a specific machinery configuration in mind, but there may be a situation when they need to be applied to a different machinery design. The new equipment configuration may affect the model prediction accuracy, which is typically different from the prior one. The change in data can also happen due to collecting the training and test sets from different sources or having an outdated training set due to data change over time. In this case, there would be a discrepancy across domain distributions, and naively applying the trained model on the new dataset may cause degradation in the performance. Domain Adaption (DA) can aid in such issues and implement efficient extraction of features from unlabeled equipment data, which is a prevalent problem in most real-time industrial applications (Ainapure et al., 2020). The author in Li and He (2020) presented a unique RUL prediction technique based on a deep convolutional neural network (DCNN) coupled with Bayesian optimization and adaptive batch normalization (AdaBN). The results also demonstrate that the prediction model's domain adaptability capacity has improved. One of the most common techniques to transfer learning is domain adaptation,

which assumes that the label spaces of the source and destination domains are similar. The architecture and concept of domain adaptation presented by Liu et al. (2020a) are shown in Fig. 24 (Liu et al., 2020a). Heterogeneous unsupervised domain adaptation is a naive emerging field to be worked on in the future.

#### 4.3.6. Adversarial ML

While certain machine learning models are good at predicting predictions, they may not be good at detecting unlawful intrusions. Adversarial Machine Learning (AML) models protect the model structure from adversarial assaults that endanger the predictive maintenance framework's resilience. Kumar et al. (2019) provides a list of adversarial ML attacks, from which the top four attacks with the most industrial impact are poisoning attack, Evasion attack, Trojan attack, and model extractions/ stealing attack. The findings in Li and He (2020) show that CBM systems are vulnerable to adversarial machine learning assaults, necessitating security measures. According to the timing of the attack, the approaches employed by hackers for adversarial machine learning may be classified into two categories: Data Poisoning: To deceive the output model, the attacker modifies the labels of certain training input instances. Model Poisoning: After the model is constructed, the hacker causes it to provide incorrect labeling by utilizing a perturbed instance. The adversarial machine learning attack is depicted in Fig. 25 (Abadi,

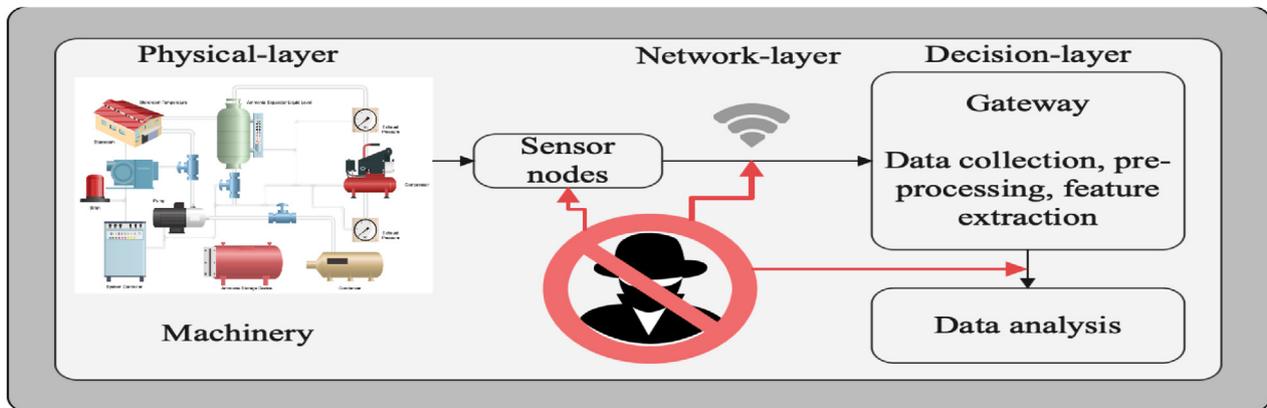


Fig. 25. Example of adversarial ML attack.

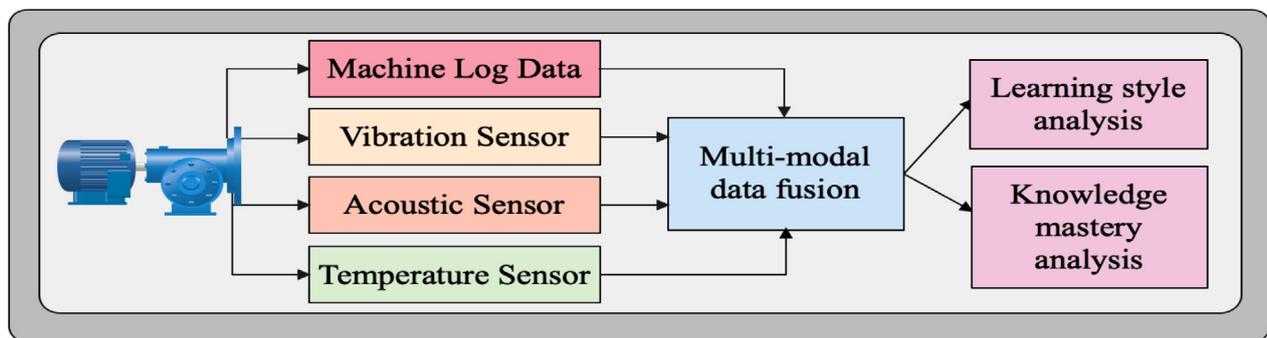


Fig. 26. The architecture of multi-modal perception with data fusion and analysis.

2021; Catak and Yayilgan, 2021). Blockchain-enabled (Shidne et al., 2021) reliable machine condition monitoring and fault diagnosis model can be a domain for future research.

#### 4.3.7. Multi-modal data fusion

Compared to single modalities (i.e., unimodal) systems, multimodal deep learning systems employ several modalities, including vibration, temperature, pressure, AE, etc., and perform better. Representation, translation, alignment, fusion, and co-learning are all aspects of multimodal machine learning. Some of the challenges in the multimodal analysis include missing modalities, noisy data, a lack of annotated data, inaccurate labeling and scarcity during training–testing, domain adaptability for diverse datasets, and interpretability of results (Rahate et al., 2022). Fig. 26 (Yang and Zhang, 2019) shows the multi-sensor data collection for Multi-Modal Data Fusion (MMDF). From a future perspective in the context of Industry 4.0, the majority of multi-modal data in smart manufacturing setups must be gathered in dynamic settings, implying that the data itself varies. Also, it should rate the essential modalities in the diagnosis of the fault.

### 5. Recommendations for future work

Apart from the above-mentioned future research work in each current advancement, the authors would like to suggest a few other possible research directions in Data-Driven Multi-fault diagnosis of Industrial rotating machines. Table 17 describes the research gap identified and the corresponding future direction for the upcoming research. It should be mentioned that the range of this study is limited to a sample of research journals and keywords. It is proposed that the procedure outlined here be repeated for the same research theme in the future, with more databases taken into account.

### 6. Conclusion

This study focuses on data-driven predictive maintenance in industrial rotating machinery for multi-fault detection. According to the available literature, multi-fault diagnosis is still a developing field with much room for advancement in Industry 4.0. The study examines several open research topics that researchers in this field are grappling with by implementing a systematic literature review on a Data-driven approach for multi-fault diagnosis of Industrial Rotating Machines. This review was implemented using the “Preferred Reporting Items for Systematic Reviews and Meta-Analysis” (PRISMA) method. The article discusses all aspects of the physical layer: the machinery and the sensors, followed by the various data acquisition methods employed to collect the data. There is also a systematic analysis of available online datasets in this field. The paper has also focussed on signal processing techniques, mainly feature extraction methods such as time domain, frequency domain, and time–frequency domain features. Authors have also covered the topic of multi-sensor data fusion at different levels, viz., the data-level, feature-level, and decision-level fusion. There is also a great focus on various data-driven and hybrid approaches implemented by the previous researchers. Covering the recent advancements in a data-driven approach for multi-fault diagnosis, the authors have identified the significant challenges faced in this domain and given the corresponding solution. Finally, the authors conclude the paper with the infographic diagram covering all the above aspects and addressing the future scope in the domain. The authors have tried to evaluate all aspects of data-driven multi-fault diagnosis in predictive maintenance and believe that this survey will assist the researchers, the essential background in future research directions.

**Table 17**  
Research gap and future direction for multi-fault diagnosis in industrial rotating machines.

Sr. No.	Research gap	Future direction
1	Robust data collection is lacking as the researchers mainly focus on either online data (which is unimodal) or not considering the multi-modal aspect of the data.	There is a need to use multi-sensor data fusion or multimodal analysis to experiment with multi-fault diagnosis in predictive maintenance.
2	There is extensive research on bearing faults. However, industrial rotating machines also have faults like unbalance, misalignment, looseness, etc., which are related to each other. They are equally essential to be considered along with bearing faults for the study to be complete.	Research should now focus on the multi-fault aspect of fault diagnosis in rotating machines.
3	Exhaustive research has been implemented using standard datasets available online. However, real-time industrial conditions are continuously changing. That is why most AI models fail when they are implemented in a real-time industrial environment.	There is a high need to use domain Adaptation and transfer learning to the models to reduce the domain dependence of the model. Also, one must consider industrial conditions while working on their test setup (avoid online data) generating benchmark datasets.
4	Validating the proposed algorithm or model in the real-time industrial environment lacks most of the articles published.	There is a need to prove the algorithm's accuracy by validating it in a real-time industrial environment.
5	Research in Digital twin +predictive maintenance is very little and still in the phase of development.	Digital twin, emerging technology and very effective in predictive maintenance, is a new challenge for upcoming researchers.
6	Many researchers use a data-driven model or a model-based technique to compute the fault diagnosis, which may contain prediction mistakes due to individual models' uncertainty.	A hybrid data-driven strategy combined with hybrid decision-making algorithms might reduce fault prediction mistakes.
7	Changes in sensor operating conditions, disruption due to big equipment starting, high-frequency interference, and other factors taint sensor signals. As a result, it is difficult to eliminate or filter noise from raw signals. Also, the dataset is imbalanced or missing.	Integrated de-noising based on energy-correlation analysis and wavelet transform packet can be used to overcome industrial sensor signal de-noising. GANs can also be implemented to generate missing data or imbalanced data synthetically.
8	Model optimization is needed.	Reinforcement learning, an ML technique where the model learns through trial and error to choose the best course of action, can be used for model optimization.
9	As discussed earlier, cloud computing is prone to several security issues where AI/ML models can be attacked in several ways.	The development of adversarially resilient AI/ML models for industrial applications is still a topic of research that has to be addressed. Balance of cloud, as well as Edge computing, can also be one of the solutions. Edge computing allows data to be processed locally (i.e., near the collecting devices), reducing bandwidth and latency significantly, and it is also more secure.
10	There is also a need to know why an AI model has come up with a particular decision.	Explainable AI is also a potential future direction to focus on, as discussed earlier.
11	IoT devices are anticipated to exceed several trillion in the following years, posing significant performance and data monitoring problems (Younan et al., 2020).	Another critical challenge that might be investigated in the future is scalability.
12	Energy and hardware constraints are two of the most critical roadblocks to ML adoption in Industry 4.0.	Research is required to improve and optimize energy usage and conservation in IoT devices (Younan et al., 2020). In addition, real-time ML through online or incremental learning can also be further studied.
13	Representation of a large amount of data generated from multiple sensors is challenging to manage.	Knowledge Graphs (set of datapoints linked by relations) is a powerful way of representing data that can be built automatically and can then be explored to reveal new insights about a domain (Hossayni et al., 2020).

### CRediT authorship contribution statement

**Shreyas Gawde:** Data curation, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Shruti Patil:** Conceptualization, Investigation, Project administration, Resources, Supervision, Visualization, Writing – review & editing. **Satish Kumar:** Conceptualization, Investigation, Project administration, Supervision, Validation, Writing – review & editing. **Pooja Kamat:** Investigation, Project administration, Supervision, Writing – review & editing. **Ketan**

**Kotecha:** Conceptualization, Project administration, Resources, Visualization, Writing – review & editing. **Ajith Abraham:** Investigation, Project administration, Resources, Supervision, Writing – review & editing.

### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

The authors have done systematic literature analysis on the available literature from Scopus and WoS. The literature obtained for analysis was extracted using the keywords specified in the article.

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