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Advancements in Condition Monitoring and Fault Diagnosis of Rotating Machinery: A Comprehensive Review of Image-based Intelligent Techniques for Induction Motors

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Abstract

Recently, condition monitoring (CM) and fault detection and diagnosis (FDD) techniques for rotating machinery (RM) have witnessed substantial advancements in recent decades, driven by the increasing demand for enhanced reliability, efficiency, and safety in industrial operations. CM of valuable and high-cost machinery is crucial for performance tracking, reducing maintenance costs, enhancing efficiency and reliability, and minimizing mechanical failures. While various FDD methods for RM have been developed, these predominantly focus on signal processing diagnostics techniques encompassing time, frequency, and time-frequency domains, intelligent diagnostics, image processing, data fusion, data mining, and expert systems. However, there is a noticeable knowledge gap regarding the specific review of image-based CM and FDD. The objective of this research is to address the aforementioned gap in the literature by conducting a comprehensive review of image-based intelligent techniques for CM and fault FDD specifically applied to induction motors (IMs). The focus of the study is to explore the utilization of image-based methods in the context of IMs, providing a thorough examination of the existing literature, methodologies, and applications.Furthermore, the integration of image-based techniques in CM and FDD holds promise for enhanced accuracy, as visual information can provide valuable insights into the physical condition and structural integrity of the IMs, thereby facilitating early FDD and proactive maintenance strategies.The review encompasses the three main faults associated with IMs, namely bearing faults, stator faults, and rotor faults. Furthermore, a thorough assessment is conducted to analyze the benefits and drawbacks associated with each approach, thereby enabling an evaluation of the efficacy of image-based intelligent techniques in the context of CM and FDD. Finally, the paper concludes by highlighting key issues and suggesting potential avenues for future research.

Keywords: Condition Monitoring (CM), Fault Detection and Diagnosis (FDD); Induction Motor (IM), Intelligent Diagnosis; Rotating Machinery (RM).

1. Background

Nowadays, rotating machinery (RM) [1] is integrated in a variety of manners throughout the industries worldwide [2]. RM has been used in many industrial applications such as chemical, power, petroleum, nuclear, mining processing plants, and factories [3, 4]. Abrupt and unexpected machinery breakdowns can pose hazardous risks, significantly damaging the system [5]. Therefore, actively following up on the availability and reliability of the machinery along with the whole setup is an essential and critical element [6].

However, a mapping between motor signals and the motor's fault condition indicators must be established for condition monitoring (CM) and Fault detection and diagnosis (FDD) techniques. It has never been simple to categorize motor conditions or gauge the severity of problems from signals, and various circumstances influence these activities. Researchers have recently shown a strong interest in IM- CM and fault identification [7, 8]. Condition-based maintenance (CBM) plays a vital role in industries, as it allows for proactive and targeted maintenance strategies based on the actual condition of equipment and machinery. By continuously monitoring the health and performance of assets, CBM enables timely maintenance interventions, minimizing unplanned downtime, optimizing maintenance schedules, and reducing overall costs. [9]. Moreover, CM, FDD, and fault prognostics of RM [10, 11] have a significant role in industries to monitor the health diagnosis of a fault and its prognosis [12]. Figure. 1 shows the components of CBM, while Figure. 2 highlights the process of CBM [13].

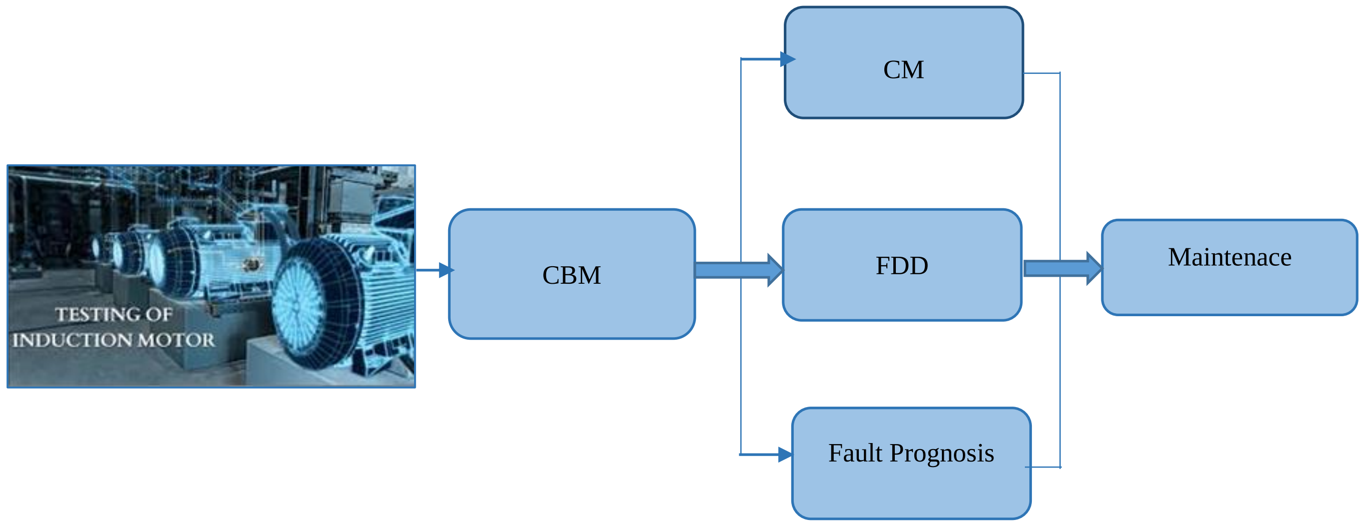

Figure 1. The components of CBM

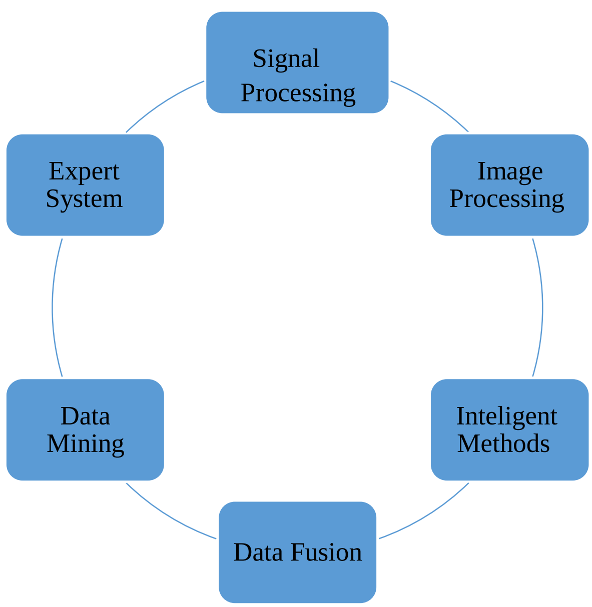

Figure. 2. The process of CBM.

Moreover, a diverse range of RM types exists, including helicopters, pumps, turbines, motors, generators, gearboxes, engines, actuators, compressors, bearings, blowers, and expanders, as shown in Figure. 3 [14].

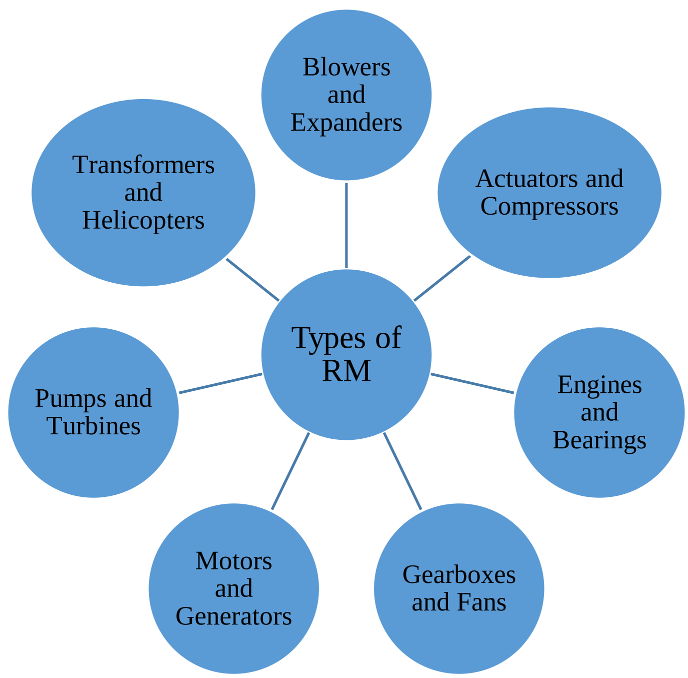

Figure. 3. Different types of RM

Many analyses have been used and investigated to diagnose and detect the faults of RM, such as [15]:

I. Temperature analysis [16]
II. Vibration analysis [17]
III. Noise analysis [18]
IV. Radio-frequency (RF) analysis [19]
V. Infrared analysis [20]
VI. Sound and acoustic emission analysis [21]
VII. Current and voltage analysis [22]
VIII. Electromagnetic field analysis [23]
IX. Oil analysis [24]
X. Pressure analysis [25]
XI. Ultrasound analysis [26]

Electrical energy is transformed into mechanical energy by the electric motor. These motors are widely utilized in applications, including pumps, fans, lifts, electric vehicles, steel mills, and cement plants. They constitute the backbone of contemporary industry. Despite many advantages, these drive systems and induction motors (IMs) are prone to many defects. To assure dependable operation, IM manufacturers and users initially relied on straightforward protection techniques like over-current and over-voltage [27]. However, the need for IM- CM has recently increased due to the widespread use of automation and the resulting decrease in direct human-machine interaction to oversee the motor drive system operation. The motor drive system experiences minimal downtime and quick unplanned maintenance due to early detection of developing issues and accurate diagnosis. Motor drive systems can curtail financial losses and avert severe outcomes.

IMs are a crucial part of many industrial processes and are regularly included in machinery and industrial processes that are available for purchase. However, environmental, operational, and installation concerns may work together to hasten motor breakdown far more quickly than the intended motor lifetimes. Numerous types of defects can occur with IMs. These categories are broadly described as failures of the bearing, rotor, windings, end rings, eccentricity-related, and stator faults as shown in Figure. 4 [28].

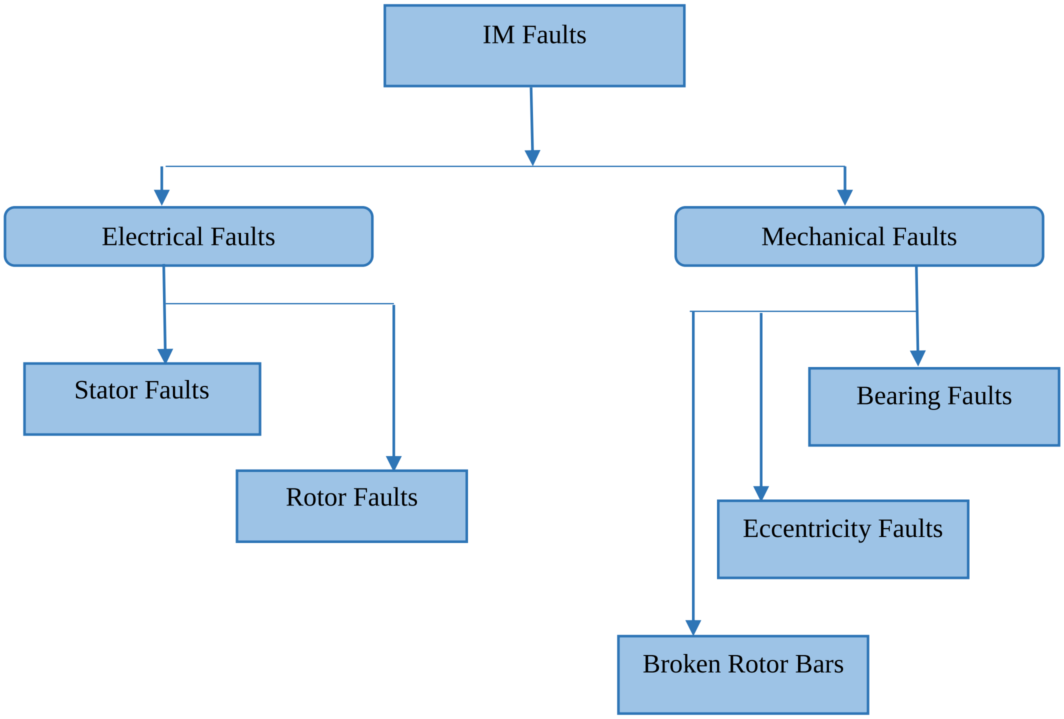

Figure 4. IM faults

As shown in Figure 1, there are two groups of IM faults: mechanical and electrical. CM must concentrate on failure modes exhibiting slow failure sequences and their underlying causes. [29]. A recent reliability paper illustrates how IM defects are distributed and also lists the principal defect distribution for IMs as bearing (41%), stator winding (37%), rotor bar (12%), and shaft/coupling other (10%) as shown in Figure. 5. That is based on Electric Power Research Institute (EPRI) , [30, 31].

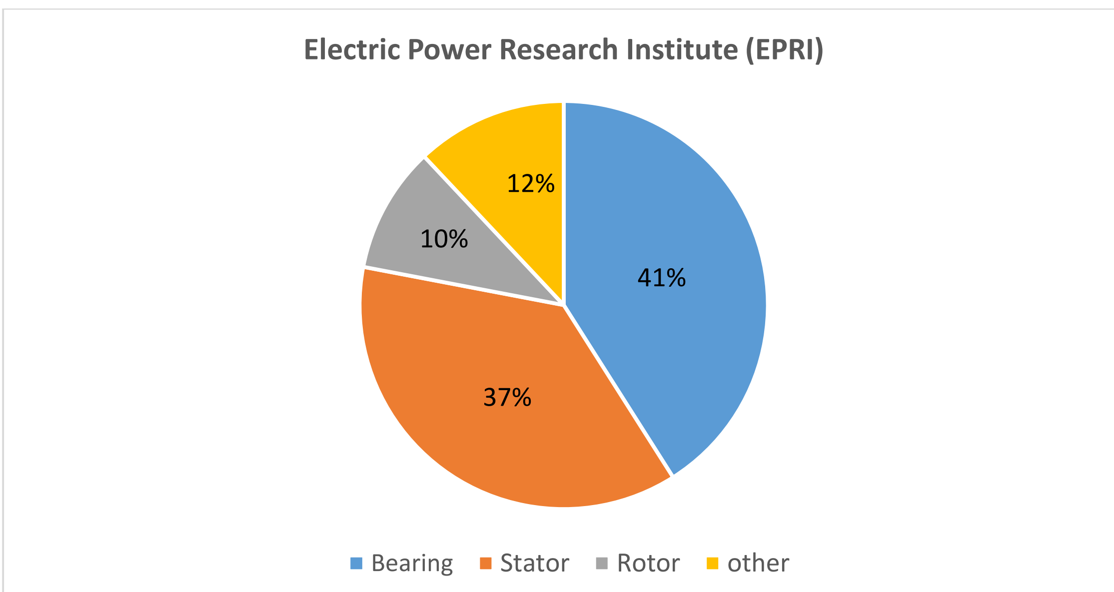

Figure 5. Percentage Failure of IM Faults

Unlike traditional methods of CM and FDD, which typically rely on one-dimensional space analysis (e.g., vibration analysis, sound analysis), image-based techniques offer the advantage of achieving two-dimensional space analysis [32]. By employing image-based methods, the analysis extends beyond a single dimension and encompasses a broader spatial domain. In traditional CM and FDD approaches, signals such as vibrations or sounds are analyzed along a single axis or time domain (TD). These methods provide valuable insights into the condition of the monitored system but are limited in their ability to capture spatial information. On the other hand, image-based techniques convert the signals into two-dimensional representations, allowing for the extraction of spatial patterns and correlations. By transforming the signals into images, image-based techniques enable the application of various image processing and analysis tools [33]. These tools can leverage the spatial information embedded in the images to detect anomalies, identify patterns, and extract relevant features.

The two-dimensional representation offers a richer and more comprehensive understanding of the system's behavior and condition, enabling more accurate and detailed analysis. The use of image-based techniques in CM and FDD expands the analytical possibilities by considering the spatial distribution of signals. This approach is particularly advantageous in scenarios where spatial relationships and patterns play a crucial role in identifying faults or abnormalities. It allows for the detection of localized anomalies, spatial variations, or patterns that may go unnoticed in traditional one-dimensional analysis. Furthermore, image-based techniques provide a visual representation of the system's condition, facilitating intuitive interpretation and communication of the results to stakeholders. By incorporating spatial information, image-based techniques can capture complex fault patterns that may occur simultaneously in different regions of the system, enabling a more comprehensive assessment and diagnosis of the overall health. [34].

The objective of this paper is to conduct a comprehensive review study on the techniques and methodologies used for CM and FDD of IMs. Specifically, the manuscript aims to explore the application of image-based intelligent approaches for CM and FDD of IMs. The study seeks to provide an overview of the existing research, identify the advantages and limitations of different techniques, and highlight the potential of image-based methods in enhancing the accuracy and efficiency of CM and FDD of IMs. Additionally, the manuscript evaluate the effectiveness of image-based intelligent techniques for improving fault diagnosis accuracy. The review study also intends to identify potential areas for future research and development.

2. Introduction of CM and FDD

Although the main emphasis of this review is centered on image-based methods for CM and FDD, it is important to acknowledge the existence of other viable alternatives within this domain. These alternatives encompass a diverse range of techniques, including traditional vibration analysis, acoustic emission monitoring, and electrical signature analysis. Each approach offers distinct advantages and finds application in various scenarios. For instance, vibration analysis has long been considered a conventional approach for detecting mechanical faults, leveraging the analysis of vibration signals to identify abnormalities in the IM's operation. On the other hand, electrical signature analysis provides a valuable tool for identifying electrical and rotor-related issues by analyzing electrical signals and waveforms generated by the IM.

By considering these alternative techniques, practitioners and researchers can explore a broader spectrum of CM and FDD methodologies tailored to their specific needs and objectives. The choice of method can significantly impact the outcomes of CM and FDD efforts. It depends on several factors, including the type of motor, the specific fault modes of interest, available resources, and the desired level of automation. As discussed in this review, image-based methods offer distinct advantages, such as early FDD, precise fault localization, and compatibility with other sensor data, making them valuable to the array of available techniques. By shedding light on these alternatives and their respective merits, we aim to provide readers with a comprehensive understanding of the diverse approaches available for CM and FDD, enabling them to make informed choices based on their specific needs and objectives.

In the field of CM and FDD, data-based and model-based methods are two primary approaches utilized for analysis and decision-making. Data-based methods, as described in reference [35], focus on utilizing historical or real-time data collected from the system to identify patterns, correlations, and anomalies indicative of faults or changes in the system's condition. These methods often involve statistical analysis, machine learning (ML) algorithms, or signal processing techniques to extract relevant information from the data and make predictions or classifications based on observed patterns. On the other hand, model-based methods, as outlined in reference [36], involve developing mathematical or physical models that capture the behavior and dynamics of the system under normal and faulty conditions. These models are typically based on known principles, equations, or system dynamics, and they are used to simulate the system's response and compare it with the actual measured data. Model-based methods often require a good understanding of the system and its underlying physics, and they rely on the accurate representation of the system's dynamics to detect and diagnose faults. Moreover, many researchers have introduced model-based FDD [37]. Over the years, several data-based CM and FDD techniques have been introduced and developed, as shown in Figure. 6. Moreover, several studies and experiments have been performed, including:

I. Signal processing-based techniques [38]

II. Intelligent techniques [39]
III. Data fusion techniques [40]
IV. Data mining techniques [41]
V. Expert Systems [42]
VI. Image processing-based techniques [43]

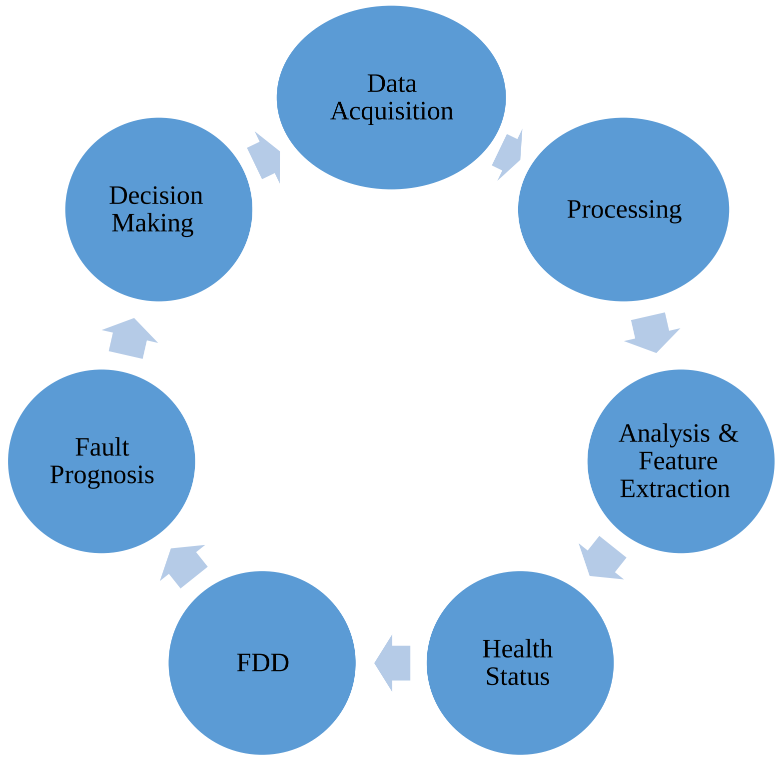

Figure. 6. CM and FDD techniques

I. Signal processing- based techniques

In the TD [44], many methods have been applied, including entropy analysis [45], envelope analysis [46], statistical analysis [47], chaotic model [48], regression analysis [49, 50], adaptive noise [51], spectral analysis [52], order tracking [53, 54], cepstrum methods [55], park's vector phase [56], amplitude change method [57], skewness [58], kurtosis [59], crest factor, [60] and histogram analysis [61], mahalanobis distance [62], Gaussian mixture [63], and Walsh transform [64].

Many methods have been applied in the frequency domain, such as Fourier transform (FT) [65], power spectral density, and damping ratios. Machine current signature analysis (MCSA) based on FFT [66],time–frequency analysis (TFA) methods [67], is the crux of CM and FDD of RM. Signal frequency identification, dealing with nonstationary signals, and time-variant features are the main advantages that make TFA an effective tool for CM and FDD.

Various TFA methods have been proposed and introduced, including Short-Time Fourier transform (STFA) [68], empirical mode decomposition EMD [69], ensemble empirical mode decomposition (EEMD), complete ensemble empirical mode decomposition (CEEMD) [70], variational mode decomposition (VMD) [71], variational nonlinear chirp mode decomposition (VNCMD) [72], wavelet transform (WT), wavelet packet decomposition (WPD), empirical wavelet transform (EWT) [73], Wigner–Ville distribution [74], Cohen class distributions [75], adaptive kernel [76], bilinear TF distribution [77], TF demodulation [78], Gabor representation [79], spectrogram, music signals, chirplet transform [80], curvelet transform [81], instantaneous phase [82], ambiguity function, multiresolution analysis [83], Hilbert-Huang transform [84, 85], and Park and Concordia transform. Many valuable review and survey papers are available in term of signal processing techniques in CM and FDD for motors [86, 87], gearboxes [88, 89], and wind turbines [90]. Artificial intelligent (AI) techniques [91] are mainly used for CM, FDD, and classification for RM. The main AI methods include artificial neural networks (ANN), fuzzy logic systems (FLS) [92], genetic algorithms (GA), support vector machines (SVM) [93], and deep learning (DL) algorithms [94]. For more details, many AI reviews are available in the literature [95, 96] for motors [97], gearbox [98], and wind turbines [99]. Data fusion techniques are widely used nowadays to achieve more accurate CM and FDD results. The data fusion process aims to collect data from multiple sensors, such as vibration, acoustic, current, voltage, and temperature [100]. Crucially, CM and FDD primarily focus on identifying and detecting faulty patterns. Therefore, CM and FDD's data mining algorithms are highly used [101]. Furthermore, a valuable review paper is available in [102]. Nowadays, knowledge-based systems are becoming very important and common. Expert diagnostic systems for FDD are proposed and introduced in [103-109]. More and more valuable information is available in [110].

II. Intelligent techniques

To precisely and effectively detect and diagnose faults in IM, CM and FDD are required. The most common list of intelligent techniques that can be applied to CM and FDD are listed below:

ML : a branch of AI known as ML that enables computers to learn from data and make predictions or judgments based on that data. By examining data from various sensors, including vibration, temperature, and current sensors, ML can be used to discover and diagnose defects [111, 112]. Historical data can be used to train ML algorithms to find trends and anomalies that point to problems .

ANNs: a class of ML models that are based on how the human brain functions. By examining sensor data and predicting the health status of the equipment, ANNs can be employed for CM and FDD [114, 115]. By analyzing sensor data and locating the source, ANNs can also be utilized for defect diagnostics [116].

Fuzzy logic: Fuzzy logic is a branch of mathematical logic that deals with approximative rather than precise reasoning. By examining sensor data and making decisions based on the degree to which the data are members of different categories, fuzzy logic can be employed for CM and FDD [117, 118]. By examining sensor data and determining the fault's most likely source, fuzzy logic can also be utilised to diagnose faults.

Expert systems: computer programs that simulate the decision-making process of a human expert in a specific field. By analyzing sensor data and providing maintenance or repair recommendations based on the machinery's present state of health, expert systems can be used for CM and FDD [119, 120]. By examining sensor data and offering suggestions for troubleshooting and repairs, expert systems can also be used to defect diagnosis.

GA: a class of optimization algorithms imitates natural selection called GA.It can be used for CM and FDD by adjusting the parameters of a ML algorithm to increase accuracy and efficiency. GA can also diagnose faults by identifying the fault's most probable cause from a list of potential possibilities [121, 122].

While intelligent-based mechanisms offer significant advantages in CM and FDD for IMs, they have certain limitations. These include computational complexity, sensitivity to data quality and quantity, the need for specialized expertise, and limited model interpretability. Overcoming these limitations and enhancing the efficiency and accessibility of intelligent-based systems are active research areas in the field.

III. Data fusion techniques

To increase the precision and dependability of CM and FDD of IM, data fusion techniques are used to aggregate data from different sensors or sources. The following data fusion methods can be applied to CM and FDD for IM:

Model-based fusion: model-based fusion combines data from many sources using mathematical models. The models are being based on mathematical learning algorithms, statistical analysis, or physical principles. To increase the precision and dependability of IM by using CM and FDD, model-based fusion can be utilized to merge data from various sensors, such as vibration, temperature, and current sensors [123, 124].

Sensor fusion: to increase the precision and dependability of CM and FDD, sensor fusion merges data from various sensors. To provide a clearer picture of the machinery's health, sensor fusion can merge data from many types of sensors, including vibration, temperature, and current sensors [125, 126].

Data-driven fusion: combines data from many sources using ML methods. Data-driven fusion increases the precision and dependability of CM and FDD and merges data from various sensors, such as vibration, temperature, and current sensors [127, 128]. ML algorithms can be trained using historical data to find trends and anomalies that point to defects.

Decision fusion: to increase the precision and dependability of CM and FDD, decision fusion integrates the judgments or suggestions given by several algorithms or experts. Decision fusion has being used to merge the recommendations produced by several algorithms to provide a more precise and trustworthy diagnosis of defects, such as ML algorithms and expert systems [129, 130].

Feature-level fusion : to increase the accuracy and dependability of CM and FDD , feature-level fusion combines the features or characteristics extracted from data by various algorithms or sensors. To provide a more clearer picture of the machinery's health, feature-level fusion can merge the features gathered from several sensors, including vibration, temperature, and current sensors [131].

These are a few data fusion methods that can be applied CM and FDD. The exact application and the information determine the strategy to use. The objective is to aggregate information from many sources in a way that offers a more precise and trustworthy picture of the machinery's state of health.

IV. Data mining techniques

For CM and FDD, for IM, data mining techniques can be used to analyse huge amounts of data and find patterns or anomalies that might point to the presence of defects. The following data mining methods can be applied for CM and FDD:

Association rule mining: in order to find patterns or connections between various variables in a dataset, association rule mining is performed. For CM and FDD, association rule mining can be utilised to find patterns in sensor data that might point to the presence of defects [132].

Clustering: based on shared traits or properties, clustering is used to put comparable data points together. For CM and FDD, clustering can be used to collect data from many sensors, including vibration, temperature, and current sensors, and identify trends that can indicate the presence of defects [133].

Classification: data points are classified according to their qualities or traits to place them in predetermined groups. For CM and FDD, classification can be used to categorize sensor data into groups representing the machine's health condition, such as normal, warning, and defect [134].

Regression analysis: it is used to determine how variables are related to one another and to forecast a variable's value based on the values of other variables. For CM and FDD, regression analysis can be utilized to forecast the health status of the equipment based on the values of various sensor data [135].

Time series analysis: it is used to examine data gathered over time, such as sensor data from turning machinery. Time series analysis can be utilized for CM and FDD to find trends or abnormalities in sensor data that might point to a problem [135, 136].

These are a few data mining methods that can be applied to CM and FDD. The exact application and the information determine the strategy to use. To prevent equipment failure and downtime, it is important to find patterns or abnormalities in sensor data that may indicate problems. Using this information, maintenance or repair choices may then be made.

V. Expert Systems

Expert systems are AI programs that employ knowledge and logic to address issues that would typically require the expertise of a human. By combining the knowledge of domain experts and using this information to diagnose defects and prescribe maintenance or repair activities, expert systems can be used for CM and FDD [137]. Here are some instances of expert systems being applied as CM and FDD:

FDD: diagnose defects using expert systems by combining domain experts' expertise and applying that knowledge to understand sensor data. Expert systems can analyze sensor data to identify patterns or abnormalities that could indicate the presence of defects and provide suggestions for repairs [138].

Prognostics: expert systems can be utilized for prognostics by combining domain experts' knowledge and utilizing this information to forecast the machinery's future state of health. Expert systems can forecast when faults develop and recommend maintenance or repair steps to avoid equipment failure and downtime using sensor data and historical data [139].

Maintenance planning: by combining the knowledge of subject matter experts and applying this information to optimize maintenance schedules, expert systems can be used to plan maintenance tasks for rotating machinery. Expert systems can offer the best maintenance plans to reduce downtime and maintenance expenses using sensor data, historical data, and knowledge of the machinery.

CM : by combining the knowledge of subject matter experts and using this information to interpret sensor data, expert systems can monitor the condition of rotating machinery. Expert systems can identify patterns or irregularities in sensor data pointing to defects and suggest upkeep or repair measures [140].

Root cause analysis : by leveraging the expertise of subject-matter experts and applying this knowledge to identify the root causes of defects, expert systems can be utilized for root cause analysis of rotating machinery. Expert systems can pinpoint the source of faults and suggest maintenance or repair steps to prevent them from reoccurring using sensor data, historical data, and an understanding of the machinery.

These are a few instances of expert systems applied CM and FDD. Expert systems may include domain specialists' knowledge and utilize it to diagnose defects, forecast the machinery's future health status, optimize maintenance schedules, track the machinery's condition, and conduct root cause analysis. The objective is to utilize professional knowledge to make precise and trustworthy recommendations for maintenance or repair operations to stop equipment breakdown and downtime.

3. Image-based CM and FDD for IM

Image-based methods have gained significant attention in the field of CM and FDD for IMs due to their potential to enhance maintenance practices. These methods utilize visual information obtained from images or videos of the IMs to assess their health condition and detect potential faults. By analyzing the structural integrity, vibration patterns, thermal signatures, or other visual features of the IMs, image-based techniques can provide valuable insights into the operational state of the motors. One of the key advantages of image-based CM and FDD is the capability for early FDD. Visual inspection through images allows for the identification of subtle changes or anomalies in the motor components, such as cracks, wear, or deformations, which may indicate impending faults. This early detection enables timely maintenance interventions, reducing the risk of unexpected failures and minimizing downtime. Moreover, image-based techniques offer precise diagnostic capabilities. By analyzing images or video sequences, experts can visually inspect the IMs and accurately diagnose specific types of faults, such as bearing faults, stator faults, or rotor faults. This detailed diagnostic information aids in determining the root causes of the faults and facilitates the development of targeted maintenance strategies.

Furthermore, image-based CM and FDD can be seamlessly integrated with other sensor data sources, such as vibration sensors, temperature sensors, or acoustic sensors. The fusion of multi-modal data enhances the accuracy and reliability of FDD by providing a more comprehensive understanding of the IMs' health condition. This integrated approach enables a more holistic assessment of the motors' performance and facilitates a proactive maintenance approach. Despite the advantages, image-based CM and FDD also have some limitations. The quality of the images, such as resolution, lighting conditions, or camera angles, can affect the accuracy of the analysis. Additionally, the interpretation of visual information requires expertise and training, making it essential to have skilled personnel to perform the analysis. This review paper examines the increasing significance of image-based techniques in the domains of CM and FDD for IMs. Given the current technological advancements in the industry, the need for efficient and proactive maintenance practices has become paramount.

Image-based methods present unique advantages, such as early FDD, precise diagnostic capabilities, and seamless integration with other sensor data sources. By synthesizing and summarizing recent research findings, this review aims to bridge the gap between theoretical knowledge and practical applications, providing a comprehensive understanding of the current state of image-based CM and FDD and its implications across various industries. Additionally, the review highlights the advantages and limitations associated with employing images and image processing techniques in CM and FDD. Furthermore, the paper addresses key challenges faced in this area and proposes potential future research directions to further advance the field of image-based CM and FDD for IMs [141].

Nowadays, vibration images and thermal images are widely employed in the field of CM and FDD. Vibration images offer a straightforward and uncomplicated approach for assessing the health condition of RM equipment. By capturing and analyzing vibration patterns, faults and abnormalities in the machinery can be detected and diagnosed efficiently. Additionally, thermal images have gained popularity as a valuable tool in CM and FDD. They enable the visualization of temperature distributions, allowing for the identification of overheating or thermal anomalies that may indicate potential faults or malfunctions. The simplicity and ease of use associated with vibration images make them a practical choice for monitoring and diagnosing the health of RM systems [142]. The concept behind vibration images is to transform the one-dimensional vibration signal into a two-dimensional image format, thereby enabling the utilization of various image processing techniques. This conversion facilitates the representation of the vibration signal's amplitude and phase information through two distinct channels within the image, as opposed to a single channel in a separate signal. By leveraging the capabilities of image processing, vibration images offer enhanced visualization and analysis possibilities for CM and FDD applications [143]. On the other hand, thermal images have found extensive applications across diverse domains. They have proven to be valuable in areas such as surveillance, safety, medical and healthcare, military operations, mechanical and electrical maintenance, as well as energy efficiency initiatives. Thermal imaging technology enables the detection and visualization of temperature patterns and distributions, enabling the identification of anomalies, heat sources, and potential faults. This versatility has made thermal images indispensable in various industries and sectors, supporting tasks ranging from equipment inspection and maintenance to environmental monitoring and energy optimization. [144-146].

Thermal images serve as a primary indicator for CM and FDD by assessing the operating conditions based on temperature variations. The utilization of thermal images offers several significant advantages, including real-time functionality, which enables faster and more reliable decision-making processes. This real-time capability proves beneficial in reducing equipment breakdowns, system downtime, and associated maintenance costs. One of the key advantages of employing thermal images in CM and FDD is their non-invasive and non-contact nature. Thermal imaging enables temperature measurements without the need for physical contact with the equipment under inspection. This non-invasive characteristic is particularly valuable as it minimizes disruptions to normal operations and reduces the risk of damage or interference during monitoring activities. Furthermore, thermal images provide the capability for remote monitoring. By capturing temperature distributions from a distance, thermal imaging allows for monitoring activities to be conducted remotely, reducing the need for direct access to the equipment. This remote monitoring capability enhances convenience and flexibility, especially for large-scale or hard-to-reach systems. Another advantage of thermal imaging in CM and FDD is its real-time monitoring capability.

Thermal cameras can capture and process temperature data instantaneously, enabling the detection of temperature anomalies or irregularities in real time. This real-time functionality facilitates prompt action and intervention, helping to prevent potential equipment failures or malfunctions [147]. In addition to the mentioned benefits, thermal imaging provides the advantage of facilitating large area monitoring. This capability enables the assessment of temperature variations over a wide area or multiple components simultaneously. This feature proves particularly useful in monitoring complex systems or installations where multiple thermal zones need to be analyzed concurrently. By capturing thermal images, it becomes possible to observe the temperature distribution across a broad spatial extent. This allows for the identification of temperature anomalies or variations in different regions or components within a system. It becomes easier to detect potential hotspots, cooling inefficiencies, or thermal gradients that may indicate abnormal conditions or impending faults.On the one hand, computer vision and image processing techniques [148] are used in CM and FDD for feature extraction and classification stages. On the other hand, very limited studies and faults have been investigated using these terms. Although all image processing methods are considered signal processing methods, image processing is currently recognized as a separate field.

However, before discovering faults using image processing techniques, some highlights must be done first. Image enhancement [149] techniques in both spatial and frequency domains are used in CM and FDD. Image enhancement is pre-processing the image to be suited for applying feature extraction. Importantly, filtering, histogram equalization, adaptive contrast enhancement, smoothing, and sharpening are the main types and methods of image enhancement [150]. Image texture analysis [151-153] is one of the image processing fields used to extract textural features from images, such as pixel intensity, grayscale intensity, roughness, and smoothness.

Image texture analysis is widely used in CM and FDD [154, 155]. Image segmentation divides the image into multiple blocks called segments based on relevant information such as edge, boundary, object, and shapes. Edge and boundary detection technique is used to identify the boundaries and edges of objects in an image. Edge and boundary detection technique is used in CM and FDD as a feature image extraction process to seek faulty segments in an image [156, 157]. Furthermore, object tracking and shape recognition are also used to track faulty objects (segments) in an image [158, 159]. Figure. 7 shows the flow chart of the image- based intelligent CM and FDD of the IM.

Data acquisition refers to the process of capturing or collecting data from various sources or sensors. In the context of CM and FDD for bearings, stator, or rotor, data acquisition involves capturing images, such as thermal images, from an imaging device or an infrared camera. Data preprocessing is an essential step in data analysis. It involves transforming raw data into a format that is suitable for further analysis or model training. Several common techniques are used in data preprocessing, including filtering, resizing, and augmentation. Moreoverm image-based feature extraction methods in the field of computer vision and image analysis have advanced significantly with the advent of intelligent techniques such as DL. Fault classification and decision-making are crucial components of CM and FDD systems. Once a fault or anomaly is detected, the next step is to classify and identify the specific type of fault and make informed decisions regarding the appropriate actions to be taken.

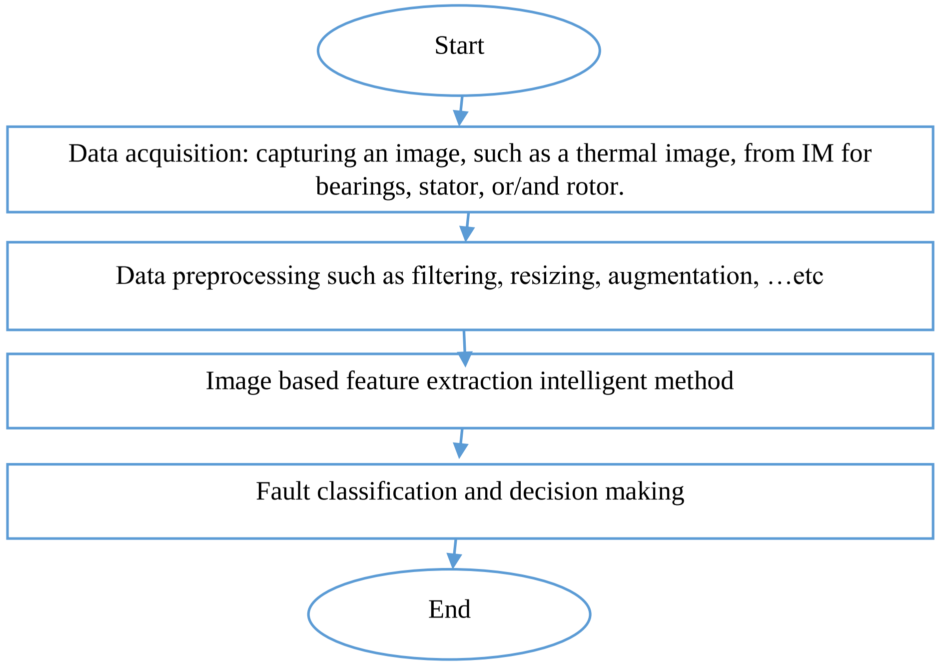

Figure 7. The flow chart of the image- based intelligent CM and FDD of the IM.

I. Image- based intelligent CM and FDD of roller bearing's

With the advancements in image processing and ML techniques, researchers have developed intelligent systems that utilize images to monitor the condition of bearings and diagnose faults. These systems can detect faults such as wear, misalignment, and defects by analyzing the visual information captured from the bearings. Integrating image-based monitoring and diagnosis techniques with IMs provides a proactive approach to ensuring the reliability and performance of these critical components. This research area holds great potential for improving the maintenance strategies of IMs, enabling early FDD and timely preventive actions, ultimately leading to enhanced operational efficiency and reduced downtime.

In [160], the method first converts the vibration signal into an image to diagnose two faults, namely, Self-priming centrifugal and axial piston hydraulic pump. The proposed approach employs a multi-disciplinary method. Moreover, automatic feature extraction and FDD in a two-dimensional space is realized. The method consists of four steps. In the first step, image transformation of vibration signal based on bi-spectrum is employed. In the second step, feature extraction based on speeded up robust features (SURF) is applied. In the third step, dimension reduction built on t-distributed stochastic neighbour embedding (t-SNE) is also applied. Finally, in the fourth step, FDD based on a probabilistic neural network (PNN) is introduced and investigated. The results demonstrate the methods' high accuracy. However, the aimed approach needs to apply to more types of machines and improve computing speed.

In reference [161], the authors propose a method for obtaining an image that captures the time-frequency relationship of the main signal elements. The method involves two main steps: EMD and principal component analysis (PCA) combined with STFT. In the first step, EMD is applied to decompose the signal into its intrinsic mode functions (IMFs). This decomposition helps to extract the signal components with different frequencies and time scales. In the second step, PCA is performed on the IMFs combined with STFT to generate the image representation. PCA is used to reduce the dimensionality of the data and extract the most significant features representing the time-frequency relationship of the signal. Finally, a support vector machine (SVM) is employed as a standard ML technique for the classification stage. SVM is known for its ability to handle high-dimensional data and effectively classify patterns based on a defined decision boundary. The combination of EMD, PCA with STFT, and SVM classification allows for the extraction of meaningful features from the signal and accurate classification of the main signal elements.

In reference [162], the authors propose a classification method that utilizes WT for feature extraction based on visual word representation. The method aims to identify local patterns in the time-frequency image of a vibration signal. The WT is applied to the time-frequency image, allowing for the extraction of relevant features that capture the local characteristics of the signal. These features are then represented using a visual word representation approach, which involves quantizing the extracted features into a set of visual words or codebook. By representing the local patterns using visual words, the classification process becomes more efficient and effective. It helps reduce the risk of overfitting, which occurs when a model becomes too specific to the training data and performs poorly on unseen data. Additionally, the visual word representation enables reliable performance in classifying the vibration signal, as it captures the essential features and characteristics of the signal. Furthermore, the proposed classification method offers the advantage of saving training time. By using visual word representation, the feature extraction and classification processes can be streamlined, leading to faster training and classification times compared to other approaches. The results of the study demonstrate the benefits of the proposed classification method. It reduces the overfitting problem, provides reliable performance in classifying vibration signals, and saves training time. These advantages contribute to the effectiveness and efficiency of the classification process in practical applications.

In reference [163], an infrared (IR) imaging technique is employed for bearing FDD. The approach utilizes IR imaging to identify different lubrication levels and detect various lubrication-related situations, such as imbalance, outer-raceway problems, and varying lubrication levels. The IR imaging method enables the visualization of temperature patterns on the bearing surface, providing insights into the lubrication condition and potential faults. By analyzing the IR images, variations in temperature distribution associated with different lubrication levels can be detected, aiding in the identification of bearing faults. To enhance the accuracy of the FDD method, novel IR imaging features are introduced and combined with the standard deviation technique. These features capture specific temperature patterns and variations in the IR images, facilitating more accurate fault detection and diagnosis. The reported accuracy of the method in reference [163] is approximately 88.25%. This indicates a relatively high level of effectiveness in detecting and diagnosing bearing faults using IR imaging and the proposed features. However, there are limitations associated with this method. One major limitation is the requirement for expensive IR cameras, which can be a significant investment. Additionally, the use of IR imaging for imbalance detection may present challenges, as it may not be as effective in identifying this specific fault type compared to other fault conditions.

In reference [164], an intelligent FDD and classification system is developed for FDD in roller bearings. The system utilizes time-frequency (TF) images and employs image processing and fuzzy logic techniques for defect classification. The TF images are generated to capture the time and frequency characteristics of the vibration signal. These images provide a visual representation of the signal's energy distribution over time and frequency domains, enabling the extraction of informative features for FDD. In the image processing stage, threshold filtering and connectivity algorithms are applied to enhance the relevant features and separate them from noise or irrelevant information. These processing techniques help to highlight and isolate the defect-related patterns present in the TF images. For defect classification, Fourier Descriptors extracted from the processed TF images are utilized. Fourier Descriptors are mathematical representations that capture the shape and frequency characteristics of an object or pattern. The Fuzzy logic approach is then employed to classify these descriptors and determine the health condition of the roller bearing. According to the researchers, the developed technique demonstrates the ability to automatically classify defects in roller bearings. The system has been successfully applied to determine the health status of roller bearings, indicating its effectiveness in FDD and classification.

In reference [165], the application of thermal imaging combined with vibration analysis for multiple bearing systems is discussed. The research involves the use of a single vibration sensor and a single temperature sensor for each bearing in the system. The technique combines vibration analysis with temperature data to improve FDD capabilities. By simultaneously monitoring the vibration signals and temperature variations of the bearings, the method aims to leverage both types of data for more accurate and reliable FDD. However, the authors of the study concluded that FDD using vibration data in combination with temperature measurements yielded better results compared to vibration data analysis alone. This suggests that incorporating temperature information enhances the effectiveness of the FDD process, enabling more accurate identification of bearing faults. Despite the benefits of the combined method, there are drawbacks associated with its implementation. Firstly, it is mentioned that the method is still expensive, likely due to the requirement of multiple sensors for each bearing, including both vibration and temperature sensors. This cost factor may limit its practical application in certain scenarios. Additionally, another limitation mentioned is that the combined method can only detect one type of fault.

Sparse representation [166] is extensively used for FDD. Sparse representation is a mathematical framework that aims to represent signals or data as a linear combination of a few essential components or atoms selected from a predefined dictionary. In the context of FDD, sparse representation is applied to analyze and process the signals obtained from various monitoring systems, such as vibration sensors or acoustic sensors. The method involves decomposing the signals into a sparse set of representative components or features that capture the essential information related to fault conditions. [167] suggests a brand-new feature extraction technique built on a sparse image representation. Fast Fourier transformation (FFT) is used to create spectrum images, and the underlying structure of the spectrum image based on vibration signals is discovered through the extraction of sparse coefficients. The raw vibration signal data features are implemented using the orthogonal matching pursuit and K-singular value decomposition algorithms. Its key benefits are this method's simplicity and a limited number of spectrum image samples. In [168], image sparse representation is applied to find the time-frequency domain sparse components in the grayscale structure of the raw image. The method demonstrates a good ability to extract the transient state.

In reference [169], an image recognition approach is applied to FDD in constant and variable speed conditions. The study utilizes both traditional bearing FDD and an additional technique called the ProbPlot via IR-AVPCA (ProbPlot via AVPCA). The traditional techniques, are employed for bearing FDD. These techniques likely involve analyzing vibration signals using established methods such as time-domain analysis, frequency-domain analysis (e.g., FFT), or statistical approaches. The ProbPlot via AVPCA technique is introduced as an additional approach. In this technique, images in the TD are generated from the vibration signal. The FFT and ProbPlot are then applied to these images. The ProbPlot method is a statistical tool used for assessing data distribution against a theoretical distribution. In this context, it is likely used to analyze the image data and identify abnormal patterns or deviations associated with bearing faults. The AVPCA (Absolute Value Principal Component Analysis) is employed as part of the ProbPlot technique. AVPCA is a variant of Principal Component Analysis (PCA) that considers the absolute values of the data. It is used to reduce the dimensionality of the image data and extract the most informative components or features. The mentioned technique is applied under both constant and variable speed environments, and it targets multiple types of bearing faults, including outer-race, inner-race, and ball faults.

In [170], the authors introduced an image recognition technique under variable conditions. This method consists of three parts. Firstly, a two-dimensional image based on a recurrence plot (RP) is obtained from the vibration signal data. Secondly, feature extraction is performed using scale-invariant feature transform (SIFT). Finally, Kernel Principal Component (KPC) analysis reduces the feature dimensionality. In the classification stage, a probabilistic neural network is applied. However, one major challenge with image recognition techniques is the speed of feature extraction, which needs to be addressed.

TF analysis, image representation, and DL approaches are combined in [171]. TF representations of the vibration data are employed to generate image illustrations. Short-time Fourier transform, wavelet transform, and Hilbert-Huang transform are used in this study. Moreover, a deep convolutional neural network (DCNN) is utilized in the grouping stage. The main advantage of using DNN in combination with an image representation method is its robustness to noise.

The reference in [170] suggests an automatic fault identification system built on image and DL. Moreover, vibration image processing and CNN techniques are applied. 2D vibration images are obtained from vibration signals and classified using the deep structure of convolutional neural network. The main advantages of this method include the ability to extract features without the need for feature extraction methods, high precision achievement, and robustness under raucous environments. Moreover, by converting the vibration signals into 2D vibration images, the system automatically extracts relevant features from the data. This eliminates the need for manual feature engineering, which can be a time-consuming and subjective process. The deep structure of the CNN model enables the system to learn complex fault patterns and achieve high precision in fault identification. DL models have shown remarkable performance in various image recognition tasks, and their application to vibration analysis can provide accurate FDD. Finally, the proposed method is robust and effective even in noisy or raucous environments. DL models, such as CNNs, are known for their ability to handle noisy data and extract meaningful information from it, making them suitable for fault identification tasks in real-world industrial settings [172].

In reference [173], a self-adaptive FDD system is presented, which utilizes infrared thermography (IRT) obtained using an FLIR thermal camera for diagnosing different conditions of roller bearings. The system employs the 2-dimensional discrete wavelet transform (2D-DWT) to analyze the IRT data. The 2D-DWT is applied to determine the decomposition level of the approximation coefficients using Shannon entropy. This allows for the extraction of relevant features from the IRT images and the identification of potential bearing faults. To enhance the effectiveness of the FDD system, a combination of genetic algorithm (GA) and nearest neighbor (NN) feature space selection approach is used. The GA is employed to select the most informative features from the IRT data, optimizing the feature subset for improved fault detection. The selected features are then used as inputs for the NN classifier, which performs the fault diagnosis based on the histograms of the chosen coefficients.The method described in the reference offers several advantages. Firstly, it is cost-effective as it utilizes an FLIR thermal camera, which is a widely available and relatively affordable technology. Additionally, the non-contact nature of IRT enables the system to operate without physical contact with the bearings, ensuring a non-intrusive monitoring approach. This can be particularly advantageous in industrial settings where accessibility to the bearings might be limited or where contact-based methods are undesirable.

In reference [174], a 2D time-domain vibration signal imaging approach is utilized for FDD. The method involves several steps to process the vibration signal and extract relevant features. First, the 2D grayscale images are obtained from the vibration signal. This involves mapping the time-domain vibration signal onto a 2D image representation. Each pixel in the image corresponds to a specific time and amplitude value of the vibration signal. Next, the segmented cycle technique is applied to the grayscale images. This involves dividing the image into individual cycles, which represent repeating patterns in the vibration signal. Segmentation helps isolate and analyze the cyclic behavior of the signal. Then, a Local Binary Patterns (LBP)-based speed invariant FDD approach is employed. LBP is a texture descriptor that characterizes the local texture patterns in an image. By applying LBP in a speed invariant manner, the method ensures robustness to changes in the vibration signal's speed or frequency. In the classification stage, the LBP histograms are used as texture descriptors vectors. These histograms capture the distribution of different texture patterns present in the segmented cycles of the vibration signal. The texture descriptors are then used as input features for a classification algorithm to classify and diagnose the faults. The use of the 2D time-domain vibration signal imaging approach, combined with the LBP-based speed invariant FDD method and LBP histograms as texture descriptors, enables effective FDD. The approach leverages the spatial and temporal information present in the vibration signal, providing a comprehensive analysis of the signal's characteristics.

In reference [175], an innovative bearing FDD technique is introduced, utilizing arbitrary and deliberate changes in shaft speed. The method employs a vibration spectrum imaging approach to analyze the vibration signal and detect bearing faults. The technique starts by converting the time-domain (TD) vibration signal into grayscale images with a best-fit dimension. This conversion process maps the amplitude and time information of the vibration signal into a visual representation, allowing for the extraction of meaningful features. Next, the grayscale images are classified based on their unique textures. Each image represents a specific state of the bearing, and different textures correspond to different fault conditions. The classification process aims to identify and differentiate these textures, enabling the detection of bearing faults. To encode the textures present in the grayscale images, the LBP method is employed. LBP characterizes the local texture patterns within an image, providing a quantitative representation of the image's texture features. Finally, a K-nearest neighbor (KNN) classifier is applied and trained using fault images obtained under various operating speeds. The classifier learns the patterns associated with different bearing faults at different speeds, allowing for accurate FDD. The utilization of arbitrary and deliberate changes in shaft speed as a bearing FDD technique, combined with the vibration spectrum imaging method, grayscale image classification, LBP texture encoding, and KNN classification, offers a novel approach to detect and diagnose bearing faults. By leveraging unique textures and speed-dependent fault patterns, the method enhances the accuracy and reliability of bearing FDD.

II. Image- based intelligent CM and FDD of stator faults

Researchers use advanced image processing and ML techniques to develop intelligent systems that can effectively detect and diagnose stator faults in IMs. Stator faults, such as winding insulation degradation, short circuits, and open circuits, can significantly impact the performance and reliability of the motor. Through the analysis of images captured from the stator, these intelligent systems can identify subtle visual indicators of stator faults, enabling early detection and timely maintenance interventions. Integrating image-based monitoring and FDD techniques for stator faults offers great potential for enhancing IMs efficiency, lifespan, and overall operational reliability in various industrial applications.

According to [176], the authers described the use of the Method of Area Selection of States (MoASoS) for attribute extraction of thermal figures to diagnose stator faults in IM. The study shows that by applying MoASoS, vectors representing the thermal images can be obtained. These vectors are then classified using two methods, namely the NN classifier and Gaussian Mixture Models (GMM). The study reports high efficiency in recognizing thermal images using this approach. However, it is important to note that there are certain limitations or drawbacks associated with this method. Firstly, the cost associated with thermal cameras can be a significant barrier to its widespread implementation. Thermal cameras tend to be more expensive compared to other imaging devices, which may pose challenges for practical deployment in certain industrial settings. Additionally, the method described in the reference focuses on single-type fault diagnosis, meaning it is designed to identify specific faults in the stator of IM. This limitation restricts the method's applicability to a narrow range of fault types, potentially limitingits usability in scenarios where multiple fault types or complex fault patterns are present. Considering these drawbacks, it is important to explore alternative approaches that address the cost limitations and enable more comprehensive fault diagnosis. For example, advancements in technology have led to the development of low-cost thermal imaging solutions, including thermal camera attachments for smartphones or relatively affordable standalone thermal cameras. These options provide more accessible thermal imaging capabilities, making it feasible to implement the method in a wider range of industrial settings. Furthermore, to overcome the limitation of single-type fault diagnosis, researchers are exploring the use of ML algorithms and advanced pattern recognition techniques. These approaches can enable the development of more robust and versatile FDD systems capable of identifying multiple fault types and distinguishing complex fault patterns.

In [177], a feature-based recognition method is proposed for diagnosing stator faults in IMs. The method comprises three stages: image composition, boundary representation, and feature extraction. The study highlights the effectiveness of the proposed method in diagnosing stator faults in IMs.In the first stage, image composition, the current stator pattern is captured and composed into an image representation. This image captures the spatial distribution of the current within the stator, providing a visual representation of the stator state. The second stage involves boundary representation, where the boundaries of the stator pattern are extracted from the composed image. Boundary extraction techniques are applied to identify and isolate the stator region of interest.

In the final stage, feature extraction, relevant features are extracted from the stator pattern boundaries. These features may include geometric properties, statistical measures, or other characteristics that capture important information about the stator state and potential faults. The main finding of the study emphasizes the effectiveness of the proposed feature-based recognition method for stator FDD in IMs. By leveraging the image composition, boundary representation, and feature extraction stages, the method provides valuable insights into the stator condition and enables the identification of faults. The significance of this method lies in its ability to provide a visual representation of the stator pattern and extract meaningful features for FDD. By analyzing the extracted features, patterns associated with specific faults can be identified, leading to accurate FDD.

In [178], a technique is proposed for identifying stator problems in three-phase IMs using the line current vector and a neuro-fuzzy classifier for boundary detection. The study also explores the application of this technique for identifying malfunctioning rotor motors based on their picture pattern. The technique involves utilizing the line current vector, which represents the current flowing through each phase of the motor, as an input to the neuro-fuzzy classifier. The neuro-fuzzy classifier is a hybrid model that combines fuzzy logic and neural network techniques to perform classification tasks. The main focus of the technique is on boundary detection, which refers to identifying the boundaries or regions of interest in the motor's picture pattern. By applying the neuro-fuzzy classifier to the line current vector, the boundaries related to stator problems can be detected. Additionally, the study mentions the application of the technique for identifying malfunctioning rotor motors. However, the specific details and methodology regarding the picture pattern analysis for rotor motor identification are not provided in the reference. The significance of this technique lies in its straightforward approach to stator problem identification using the line current vector and neuro-fuzzy classification for boundary detection. By leveraging this technique, potential stator problems in three-phase IMs can be detected and localized, aiding in the diagnosis and maintenance of the motors. It is important to note that the reference does not provide extensive details or evaluation results regarding the performance and effectiveness of the proposed technique. Therefore, further research and validation are necessary to assess its reliability and applicability in practical scenarios.

To automate the identification of fault type and severity in stator faults using time-variant electric currents, a novel approach is proposed that involves image identification of the 3-D current state space patterns in [179]. This innovative method aims to enhance the accuracy and efficiency of FDD in stator faults by leveraging the power of image analysis techniques. By representing the time-variant electric currents in a three-dimensional state space, the proposed approach captures the dynamic behavior and patterns of the currents over time. These 3-D current state space patterns are then transformed into images, allowing for the application of image recognition and classification algorithms. The use of image identification techniques offers several advantages in fault diagnosis. Firstly, it enables the extraction of spatial and temporal features from the current state space, providing a more comprehensive representation of the fault characteristics. This allows for a more accurate identification of fault types and assessment of fault severity.

III. Image- based intelligent CM and FDD of rotor faults

Researchers endeavor to build intelligent systems that has the capability to accurately detect and diagnose rotor defects through the utilization of image processing and ML approaches. Rotor flaws, including defects in rotor bars, eccentricity, and unbalance, have the potential to cause substantial deterioration in performance and mechanical breakdowns in IMs. By conducting an examination of images obtained from the rotor of the motor, these intelligent systems possess the capability to discern visual cues and recurring patterns that are indicative of faults in the rotor. This facilitates the prompt identification of such flaws, hence allowing for timely maintenance interventions. The use of image-based monitoring and fault diagnostic methods for rotor problems presents significant opportunities for improving the operating efficiency, dependability, and longevity of IMs across diverse industrial sectors.

To extract the features from the rotor in the IM using infrared image analysis, image breakdown and zone selection approach is applied in [180]. A method called diffusion level based on district choice criterion is used to identify fault representative regions and background information. To add an extra layer of extraction, fusion approach is used to look for features in certain locations. Finally, Naïve Bayes classifier and SVM are applied in the classification stage. The proposed method improved the accuracy of machinery identification by effectively removing inappropriate background data and extracting fault related data regions.

In [181], a fusion system for active magnetic rotor systems was proposed. Three kinds of features are extracted using vibration image. The first feature extraction method is a feature fusion method called the two-layer AdaBoost fault recognition method. The second extraction method is vibration images combined with two-layer AdaBoost method. Finally, the third feature extraction method is to take vibration images alone. As a result, the two-layer AdaBoost fusion method can fuse multiple features and its accuracy is better than traditional methods.

According to [182], the non-invasive method called Method of Areas Selection of Image Differences (MoASoID) is applied to extract features in the broken bar (BB) for IM using thermal images. Furthermore, NN (the Nearest Neighbour classifier), K-means, BNN (the backpropagation neural network) are used in the classification stage. The method compares multiple training sets and selects areas with the biggest changes. However, there are disadvantages to this method. Firstly, thermal imaging camera is very costly. Secondly, stator coils typically take a long time to heat up, and prolonged use of shorted coils can cause permanent damage to the analysed equipment.

In [183], image and signal processing techniques are employed to automatically diagnose BB faults. Specifically, the STFT is utilized in conjunction with the V-shaped pattern method. The STFT is a signal processing technique that allows for the analysis of frequency content variations over time. By applying the STFT to the current signals, information about the frequency components present in the signals can be extracted and analyzed. In the V-shaped pattern method, the STFT results are further processed to identify a specific V-shaped pattern. The V-shaped pattern refers to a distinctive pattern that appears in the STFT spectrogram or time-frequency plot of the current signals. This pattern is associated with certain fault conditions in the BB (bearing). Once the V-shaped pattern is identified, the area of the pattern is calculated. This area serves as a classifier to distinguish between healthy and faulty BB. By comparing the area of the V-shaped pattern to a predetermined threshold or using a machine learning algorithm, the BB can be automatically diagnosed as healthy or faulty. The significance of this approach lies in its ability to leverage image and signal processing techniques for automated BB fault diagnosis. By analyzing the frequency content of the current signals using the STFT and identifying the distinctive V-shaped pattern, the method provides a quantitative measure (area of the pattern) to differentiate between healthy and faulty BB.

In [184], In the reference you mentioned, a pattern recognition and current diagnosis technique is introduced to build a pattern vector for fault diagnosis. Additionally, the reject options method and K-nearest neighbors (KNN) rule are employed together in this technique. Furthermore, the technique aims to identify the localization of the failures. The pattern recognition and current diagnosis technique involves constructing a pattern vector that represents the current signals obtained from the system under analysis. This pattern vector captures the characteristics and patterns present in the current signals, which can be indicative of specific faults or abnormal conditions. The reject options method and KNN rule are utilized in combination for fault diagnosis. The reject options method allows for the identification and rejection of uncertain or ambiguous patterns that do not fit within the defined fault classes. This helps to improve the accuracy and reliability of the diagnosis process. The KNN rule is a classification algorithm that assigns a new data point (in this case, a pattern vector) to a particular class based on the majority class of its nearest neighbors. By comparing the pattern vector to a database of known patterns and their associated fault classes, the KNN rule can determine the most likely fault class for the given pattern vector. Importantly, the technique also aims to identify the localization of the failures. This means that it seeks to determine the specific location or component within the system where the fault or abnormality has occurred. Localization information can provide valuable insights for maintenance and repair purposes, enabling targeted interventions to address the identified failures.

Furthermore, FDD of BB using Gabor analysis of the current in transient regime is discussed in [185]. the FDD of BB is explored using Gabor analysis of the current signals in the transient regime. Various transforms, including STFT, wavelet transform, and the Wigner-Ville distribution, are utilized to obtain a 2D time-frequency interpretation of the current. Subsequently, Gabor analysis combined with the chirp z-transform is applied to investigate different fault types, resulting in a highly resolved TF image for accurate FDD. By employing these techniques and analyzing the TF representations, the authors aim to identify fault signatures and patterns associated with various types of faults in BB. This can aid in the early FDD of BB faults, facilitating timely maintenance and reducing the risk of further damage or failure.

The reference [186] introduces a feature extraction technique for phase space using boundary recognition and analysis in time series. The focus of the study is on three-phase current signals, which are measured and represented in greater detail through the generation of three images. To extract relevant features, a boundary detection algorithm is applied to all of the images. After the feature extraction stage, a fuzzy decision tree is deployed for the classification process.

This decision tree utilizes fuzzy logic principles to make informed decisions based on the extracted features. By employing this approach, the researchers aim to effectively identify multi-class defects in the system under analysis.

The findings of the study indicate that the proposed strategy proves to be effective in the identification of multi-class defects. By leveraging the combination of boundary recognition and analysis, feature extraction, and the fuzzy decision tree, the technique demonstrates promising results in accurately detecting and classifying various types of defects present in the system. Feature extraction for phase space using boundary recognition and analysis in time series is presented in [186]. Three phase current signals are measured and represented in more detail in three images. A boundary detection algorithm is applied for all images to extract the features. Finally, a fuzzy decision tree is applied on the classification stage. The findings show that the strategy is effective at identifying multi-class defects.

IV. Image- based intelligent CM and FDD of multiple faults

Recently, Researchers aimed to develop intelligent systems capable of effectively detecting and diagnosing multiple faults occurring simultaneously in the IM. Multiple/compound faults in IMs can involve different fault types, such as stator faults, rotor faults, bearing faults, and insulation degradation. These intelligent systems can identify complex visual patterns and anomalies associated with multiple/compound faults by analyzing images captured from various motor components. The integration of image-based monitoring and FDD techniques for multiple/compound faults offers great potential in improving IMs reliability, performance, and maintenance strategies. This research area requires the development of robust algorithms and comprehensive datasets to detect and diagnose complex fault scenarios accurately. The successful implementation of image-based intelligent CM for multiple/compound faults can enhance motor reliability, reduce downtime, and optimize maintenance efforts in various industrial applications.

In reference [187], the authors propose the use of two-dimensional texture analysis and local binary patterns (LBPs) for the detection of multi-faults in IMs. The technique involves obtaining 2D grayscale images from the time-domain vibration signals. To extract discriminative features from the images, the authors employ two approaches: the discriminating texture features method and LBP. These methods analyze the texture patterns present in the images and capture important information related to the faults in the IMs. In the categorization stage, a multi-class support vector machine (MCSVM) is utilized. The MCSVM is a ML algorithm that can effectively classify data into multiple classes. In this case, it is used to categorize the IM faults based on the extracted feature representations. One of the main advantages of this technique is its ability to deal with high background noise. Vibration signals in industrial settings often contain significant noise, and the proposed approach takes this into account by utilizing texture analysis and LBPs, which are robust to noise and can capture fault-related patterns even in the presence of high background noise levels.

In reference [188], the authors propose a method for fault classification using a 2D image obtained from a vibration signal. The vibration signal is first transformed into a 2D image representation. This transformation allows for the utilization of image processing techniques for further analysis. To extract local features from the 2D image, the authors employ the scale-invariant feature transform (SIFT). SIFT is a widely used algorithm for detecting and describing local features in images. It is known for its robustness to changes in scale, rotation, and illumination. Once the SIFT features are extracted, a pattern classification platform is applied to classify the faults. The SIFT feature vector serves as input to this platform, which employs a classification algorithm to assign the image to the corresponding fault class. The authors report that the proposed approach, which involves transforming the vibration signal into a 2D image and utilizing the SIFT features for classification, yields accurate results. The use of signal model-based vibration to 2D image conversion, combined with the powerful feature extraction capabilities of SIFT, contributes to the effectiveness of the method in fault classification.

In reference [189], a method for thermal image analysis is presented, which consists of three stages. In the first stage, image improvement is performed using bi-dimensional empirical mode decomposition (BEMD). BEMD is a technique that decomposes an image into different empirical mode functions (EMFs) representing different scales or frequency components. This decomposition helps to enhance the relevant features present in the thermal image. The second stage involves feature reduction using generalized discriminant analysis (GDA). GDA is a statistical technique that aims to find a lower-dimensional representation of the data while maximizing the class separability. By applying GDA to the EMFs obtained from the previous stage, the dimensionality of the feature space is reduced, retaining only the most discriminative information. Finally, in the third stage, a relevance vector machine (RVM) is employed for classification. RVM is a machine learning algorithm that performs binary or multi-class classification by modeling the relationships between the reduced feature vectors and their corresponding classes. It is known for its ability to handle high-dimensional data and provide accurate classification results. The proposed method is validated through multiple experiments conducted on driving motors, shafts, and disks. The accuracy of the thermal images, after applying the proposed method, is reported to be superior to that of the original images. This suggests that the combination of BEMD for image improvement, GDA for feature reduction, and RVM for classification effectively enhances the discriminative power of the thermal images and improves the accuracy of the classification results.

In reference [190], a smart identification approach is introduced for the classification of machine faults using data obtained from infrared thermography. The proposed system consists of two stages aimed at effectively analyzing the thermal images and identifying machine faults. In the first stage, the thermal image is decomposed using a 2D discrete wavelet transform. This decomposition technique allows for the extraction of relevant frequency components and spatial information from the thermal image, enabling a more detailed analysis of the machine's condition. In the second stage, the Mahalanobis distance and relief algorithm are employed as feature selection tools. These algorithms help identify the most discriminative features from the decomposed thermal image, reducing the dimensionality of the feature space and enhancing the accuracy of the classification. The selected salient features are then used in the classification stage of the system. SVMs and the linear discriminant technique are utilized as classifiers. SVMs are known for their ability to handle high-dimensional data and effectively classify complex patterns, while the linear discriminant technique provides a linear separation between different fault classes. The key benefit of this system is its capacity to aid in the diagnosis of various machine issues. By leveraging IRT data and employing advanced feature selection and classification techniques, the proposed approach enables accurate identification and classification of machine faults. This can contribute to timely maintenance and troubleshooting, leading to improved machine performance and reduced downtime.

4. Advanced techniques in image-based CM and FDD

In recent developments in image-based intelligent CM and FDD for IMs, researchers have started to employ metaheuristic methods. These techniques are gaining attention due to their ability to optimize complex problems and enhance the accuracy of FDD. While this paper primarily focuses on the techniques discussed earlier, it's essential to acknowledge the emergence of metaheuristic methods in this context [191].

Metaheuristic methods encompass a class of optimization algorithms inspired by natural phenomena or abstract mathematical concepts. These methods iteratively explore the solution space to find the best-fit parameters or configurations. Researchers apply metaheuristic methods to address specific challenges in image-based CM:

- Particle swarm optimization (PSO): PSO is a population-based optimization technique that simulates the social behavior of birds or particles in search of food. It has been employed to fine-tune image processing parameters and optimize feature extraction algorithms for FDD [192].

- GA: GA draw inspiration from natural selection. They are used to evolve and optimize image-based feature extraction methods and classifier parameters [193].

- Ant colony optimization (ACO): ACO is inspired by the foraging behavior of ants. Image-based CM has being applied to optimize the selection of relevant features from vast datasets [194].

- Simulated annealing (SA): SA mimics the annealing process in metallurgy. It's used to optimize complex image analysis algorithms, particularly in cases where the solution space has multiple local optima [195].

- ANNs with metaheuristics: ombining metaheuristic methods with ANNs has shown promise in improving the accuracy of FDD models. Metaheuristics help optimize the weights and architectures of neural networks [196].

Integrating metaheuristic methods into image-based CM and FDD for IMs reflects a growing interest in enhancing the efficiency and accuracy of these techniques. Researchers are exploring how these optimization algorithms can fine-tune parameters, select relevant features, and improve the overall performance of FDD models [197].

Incorporating metaheuristic methods into image-based CM and FDD toolbox opens new avenues for research and practical applications. Future studies may investigate these techniques' specific applications and benefits in different industrial contexts.

Predictive maintenance and remaining useful life (RUL) assessment: while the primary focus of this paper revolves around image-based CM and fault diagnosis, it is essential to delve into another critical dimension of predictive maintenance - the estimation of for rotating machinery. Predicting the RUL of equipment is paramount for industries aiming to maximize asset utilization and minimize downtime. In the context of image-based techniques, RUL prediction takes on a unique dimension [198].

RUL estimation with image-based data: **e**merging research in the field has illuminated the potential of image-based data in forecasting the RUL of rotating machinery. By continuously capturing and analyzing images of critical components, such as bearings or gears, subtle changes in their condition can be tracked over time. ML algorithms, including recurrent neural networks (RNNs) and long short-term memory networks (LSTMs), can be trained on historical image sequences to discern degradation patterns. When coupled with sensor data and operational context, these patterns can provide valuable insights into the RUL of machinery [199].

challenges and considerations: however, the path to accurate RUL prediction using image signals is challenging. These challenges include the need for large volumes of labeled image data, the development of robust feature extraction techniques, and the creation of predictive models that can adapt to varying operating conditions. Moreover, integrating image-based RUL prediction into existing maintenance strategies requires careful planning and validation [200].
Incorporating RUL prediction into proactive maintenance strategies underscores the transformative potential of image-based techniques. By anticipating the point at which machinery components will likely fail, maintenance activities can be scheduled with precision, minimizing downtime and optimizing resource allocation. The discussion extends to the economic benefits of this approach, emphasizing cost savings through reduced unplanned maintenance [201, 202].

The advancements in image-based intelligent CM and FDD of IMs have significant implications when combined with the Internet of Things (IoT) and remote/online monitoring [203]. Image-based intelligent CM and FDD techniques can be seamlessly integrated with IoT-enabled sensor networks [204]. By connecting IMs to a network of sensors, including cameras, thermal sensors, vibration sensors, and current sensors, a wealth of data can be collected in real-time [205]. This integration allows for a more comprehensive understanding of the motor's condition and facilitates early FDD [206]. Moreover, with the integration of IoT, image-based intelligent techniques enable remote and online monitoring of IMs. Data captured by sensors, including images, can be transmitted to a centralized monitoring system or cloud platform in real-time [207]. This allows maintenance personnel or experts to remotely access and analyze the data, monitor the motor's condition, and receive timely alerts or notifications when anomalies or faults are detected [208]. Remote monitoring eliminates the need for on-site visits, reducing costs and enabling faster response times. The combination of image-based intelligent techniques with IoT and remote/online monitoring opens up opportunities for advanced data analytics and ML. The large volumes of data collected from IMs can be analyzed using ML algorithms to identify patterns, correlations, and fault signatures. This enables automated FDD, classification, and severity assessment, providing actionable insights for maintenance decision-making and optimizing maintenance strategies. Furthermore, the integration of image-based intelligent techniques with IoT and remote/online monitoring supports proactive maintenance practices [209]. By continuously monitoring the motor's condition, analyzing images and sensor data, and applying predictive analytics, potential faults or abnormalities can be identified in advance. Proactive maintenance allows for planned interventions, reducing unplanned downtime, minimizing repair costs, and maximizing the operational lifespan of IMs. Lastly, image-based intelligent techniques, in conjunction with IoT and remote/online monitoring, enable condition-based and predictive maintenance approaches. By continuously monitoring the motor's condition, capturing images, and analyzing data in real-time, maintenance actions can be scheduled based on the actual health and performance of the motor. This approach optimizes maintenance resources, reduces unnecessary maintenance activities, and ensures that maintenance is performed when needed, leading to improved reliability and cost-effectiveness [210, 211].

5. Conclusion and future research directions

The advancements in image-based intelligent techniques for CM and FDD of IMs offer improved monitoring capabilities, non-invasive and remote monitoring, real-time analysis, and comprehensive insights into the motor's condition. These advancements have significant implications for industries, enabling proactive maintenance strategies, reducing downtime, and ensuring the optimal performance and longevity of IMs.

The contribution of the review paper can be summarised as:

Improved maintenance effectiveness: image-based CM and FDD approaches offer a more effective and dependable method for RM maintenance. Potential problems and anomalies can be identified early by utilizing images from various sensors and cameras, enabling maintenance staff to take preventative action to stop equipment failure and expensive downtime.

Early FDD: Algorithms for image analysis can spot minute alterations or anomalies in pictures of rotating machinery. These modifications might indicate that the equipment is deteriorating or creating flaws. Early detection of these problems enables planned maintenance to be scheduled, lowering expenses overall and the likelihood of unanticipated breakdowns.

Accurate problem diagnosis is made possible by image-based CM and FDD approaches, which offer extensive visual information on the state of rotating machinery. By examining the photos, experts can pinpoint specific flaws, such as cracks, wear, misalignments, or other damage. This enables targeted and effective maintenance procedures, cutting down on the amount of time needed for troubleshooting and improving the possibility that repairs will be successful.

Integration with other data sources: to provide a complete picture of the condition of the equipment, image-based CM and FDD approaches can be integrated with data from other sensors, such as vibration analyses, temperature readings, or sound signals. The diagnostic capabilities are improved, and the overall dependability of the maintenance decision-making process is increased by integrating multiple data sources.

Cost savings and extended equipment Life: The paper discussed various studies and approaches employing image-based CM and FDD techniques. These approaches aim to detect faults and anomalies in IMs at early stages, allowing for proactive maintenance. By addressing issues before they escalate, industries may avoid unexpected breakdowns, reduce downtime, optimize spare parts inventories, and extend the overall lifespan of their equipment. This may lead to benefits including increased productivity, better operational efficiency, and lower maintenance costs.

In conclusion, it can be found through this research that monitoring, spotting, and diagnosing defects in IMs, image-based CM and FDD approaches provide a potent solution. Industries can increase maintenance productivity, increase diagnostic accuracy, and achieve cost savings while extending the life and reliability of their equipment by utilising visual information and connecting it with other data sources. Future research can explore novel applications of image-based CM and FDD techniques in various industries beyond IMs. For instance, in the automotive sector, image analysis can be used to detect engine and transmission issues early. In the healthcare sector, similar techniques can aid in helping detecting issues in expensive medical equipments used preventing costly breakdowns. In renewable energy, wind turbines blades can benefit to reveal any damage caused by environmental factors using techniques discussed in this paper. Another example is using image-based CM in smart cities to detect and analyse structural defects, such as bridges.

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