Infrared Thermography Based Fault Diagnosis and Prognosis for Rotating Machines

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Abstract: Rotating machines are the crucial components of any industrial firm. The abrupt malfunctioning of such machines doesn't merely affect the process downtime moreover it leads to production loss. Therefore to minimize the operation and maintenance costs, early detection of faults is very essential. As of late infrared thermography (IRT) has picked up consideration amongst the non-destructive condition monitoring techniques for early fault diagnosis of rotating machines. IRT is one of the contactless and non-invasive condition monitoring (CM) tool with very high accuracy and reliability. Real-time temperature measurement is done in a non-contact manner with this technique. IRT has discovered its applications in paper, aerospace, nuclear, wood, plastic, and various other industries. This paper presents a state of art review describing the fundamentals of IRT, diverse induction motor (IM) faults, and their diagnosis. The paper summarizes some of the machine learning methods such as artificial neural network, fuzzy logic, adaptive neuro-fuzzy inference system, and support vector machine for the detection of bearing faults. Additionally, some deep learning methods have been discussed in this paper due to their superiority over machine learning methods in terms of feature extraction as well as their selection. Also, the future scope has been proposed for developing a complete and self-learning package for fault diagnosis, and prognosis.

Keywords: **Infrared thermography, Induction motor faults, fault diagnosis, and prognosis**

1. Introduction

Rotating machines are very crucial machine tools in any type of industrial application like in heavy industries, aeronautics, automotive, and many more. But the interruption or failure in their smooth running costs a lot to the industries [1]. So it becomes very important to avoid these faults or failures in such machines, which in turn will be beneficial to the industries in aspects like economy, time, and many more so for that prior detection of faults is very crucial [2]. IRT is widely used due it its non-contact nature, quick response, and accuracy. In IRT the thermal image indicates the faulty or non-faulty condition of rotating machines. Faults such as SM, BF, RF, etc. can be easily diagnosed by IRT [3-5]. This paper presents the various faults and their diagnosis which occurs in rotating machinery. IRT has been successfully used for a variety of CM applications which includes civil structures [6], the examination of electrical supplies [7-9], assessment of plastic deformation [10], monitoring of fatigue failure in materials [11], investigation of machinery [12-14], checking of printed circuit boards [15-17], review of vapor deposition process [18]. IRT has found its applications in various industries like paper [19], aerospace [20], nuclear [21] and wood [22].

1.1. Advantage of IRT over other technologies

IRT has overpass the other technologies due to the following advantages

- The non-contact nature of IRT helps in measuring the temperature of the hot bodies in a smooth manner.
- IRT is immune to electromagnetic interference and is highly accurate in tracking thermal targets from a distance.
- Unlike X-rays, IRT has no harmful radiation effects and therefore it can be used for a prolonged period.

Both machine and deep learning methods have been discussed in this paper. Machine learning methods include FL, SVM, ANN, ANFIS. For handling the data in data-driven fault detection, these machine learning methods are used. The drawback of machine learning methods is that they are incapable of generating discriminative features of raw data and are constantly united with the feature extraction process. To overcome that drawback, deep learning methods are preferred. The various deep learning methods which are used for the fault diagnosis are DBN, sparse auto-encoder, CNN, etc.

2. Development and Foundation of Infrared Thermography

2.1 History of Infrared Thermography

The original significance of the infrared spectrum was found in the year 1800 by Sir William Herschel through his examination for a new optical material. He first performed his experiment on a bulb made of a mercury-in-glass thermometer. Further, he continued to analyze the heating effect of the different colors of the spectrum by passing sunlight through a glass prism, there he found that the temperature readings indicate a consistent increment from the violet to the red end. In 1880 Langley designed a bolometer that improved the sensitivity of infrared detection to a greater extent. It made it possible to quantify the solar radiation intensity at various wavelengths.

2.2 Essentials of Infrared Thermography:

The actions of IRT and thermal cameras rely upon the hypothesis of thermal radiation. As per Maxwell's hypothesis, the transfer of energy takes place through electromangnetic waves. Like other waves, these waves carry the energy and travel with the speed of light.

Electromagnetic waves are described by their frequency ν (Hz) and wavelength λ (μm) as communicated in Equation (1), where c represents the speed of light in that medium.

$$\lambda = c / \nu \qquad (1)$$

As per Einstein, propagation of electromagnetic radiation takes place in the form of discrete packets known as photons and each photon carries energy e and frequency ν as expressed in Equation (2), h here represents the Planck's constant whose value is 6.625 x 10^{-34} J.s

$$e = h\nu = hc / \lambda \qquad (2)$$

In Equation (2) h and c are constants, and the photon's energy is inversely proportional to their wavelength which indicates that radiation with shorter wavelength like X-rays, ϒ-rays possesses more powerful photon energy and are highly destructive as shown in Fig.1

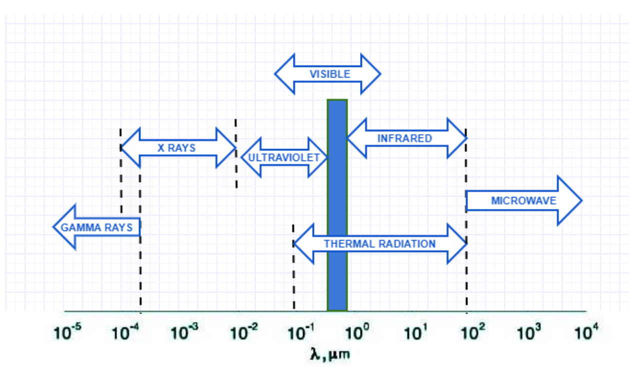


Fig 1.- Electromagnetic Spectrum.

Fig.1 shows the electromagnetic spectrum in which the wavelength varies, from 10^{-5}μm for gamma rays to 10^{4}μm for micro waves. The range of thermal radiation on the electromagnetic spectrum is very narrow. Thermal radiation emission is the manifestation of rotational and vibrational motions of atoms, molecules of a substance and these radiations are measured in the form of temperature. Therefore thermal radiation emission increases with an increase in temperature.

Stefan-Boltzmann law states that the thermal radiation emitted by a blackbody per unit time and per unit surface area is proportional to the fourth power of absolute temperature in kelvin as expressed in Equation (3), where σ is stefan's boltzmann constant and its value is 5.67 × 10^{-8} (W/m^2 K^4) , T refers to the absolute temperature in kelvin and Eb is the emissive power of the black body in (W/m^2)

$$E_b = \sigma T^4 \qquad (3)$$

Electromagnetic radiation (Ebλ) emitted by a black body can be determined using Plank's law as stated in Equation (4), C_1 and C_2 are constants with values, $C_1=2\pi hc_0^2=3.742\times10^8$ (W.μm^4/m^2) and $C_2= hc_0/k=1.439\times10^4$(μm.K), K= 1.3805x 10^{-23}(J/K) is the Boltzmann's constant, λ (μm) represents the wavelength and T is temperature measured in kelvin.

$$E_{b\lambda}(T)=\frac{C_1}{\lambda^5\left[\exp(C_2/\lambda T)-1\right]} \qquad (4)$$

The interpretation of Plank's law is shown through Fig.2 which is applicable for a surface either in vacuum or gas. The emissivity of any body at a particular wavelength λ can be defined as the ratio of the energy emitted by the body to the energy emitted by the blackbody at the same temperature as stated in Equation (5).

$$\varepsilon_\lambda=\frac{E_\lambda}{E_{b\lambda}} \qquad (5)$$

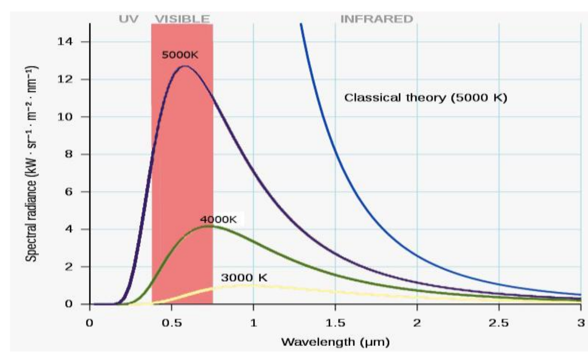


Fig 2.- Planck's law: radiant energy emitted at a different wavelength at different temperature

The following observations are drawn from Planck's law

- At a particular wavelength, the radiant energy emitted increases with an increase in temperature.
- When the radiant energy reaches the maximum value, the peak shift towards left.
- At a particular temperature, as the wavelength increases the radiant energy increases and reaches the maximum value at the peak.

When radiation is incident on a surface, some of the energy gets absorbed as well as some gets reflected whereas the remaining part gets transmitted which further defines the absorptivity(α), reflectivity(ρ), and transmissivity(τ) of that surface which are expressed in Equation (6), (7) and (8).

$$\alpha=\frac{\text{absorbed radiation}}{\text{incident radiation}}=\frac{G_{abs}}{G} \qquad 0 \le \alpha \le 1 \qquad (6)$$

$$\rho = \frac{\text{radiation reflected}}{\text{incident radiation}} = \frac{G_{ref}}{G} \qquad 0 \le \rho \le 1 \qquad (7)$$

$$\tau = \frac{\text{transmitted radiation}}{\text{incident radiation}} = \frac{G_{tr}}{G} \qquad 0 \le \tau \le 1 \qquad (8)$$

As per the first law of thermodynamics, the summation of the energy absorbed, reflected, and transmitted must be equal to the energy incident on the body as expressed in Equation (9)

$$G_{abs} + G_{ref} + G_{tr} = G \qquad (9)$$

If we divide all terms in Equation (9) by G we get another simplified Equation (10) which shows that sum of absorptivity, reflectivity, and transmissivity for a particular surface is equal to 1

$$\alpha + \rho + \tau = 1 \qquad (10)$$

3. Foregoing Research

CM of rotating machines has pulled the considerations of authors for more than thirty years. The primary arrival of CM of electrical rotating machines, composed by Tanver and Penman was published in 1987 [23]. CM of mechanical faults in rotating machines is of extraordinary hugeness to give superior quality and ensure excellent production and flexibility [24]. CM is an approach towards observing a parameter (temperature, vibration, torque, etc.) of a condition in rotating machines to distinguish a considerable change which indicates a rising fault. It is a significant part of predictive maintenance. The utilization of CM permits maintenance to be planned, or other measures to be taken to avoid substantial damages and prevent its consequences. CM techniques are generally utilized on rotating machines, auxiliary systems, and machines like pumps, compressors, gearboxes.

Failure of machinery is the lack of ability of a machine to execute its necessary function and failure is always machine explicit. The deficiencies could be in design, processing, assembly or it may be due to unsuitable maintenance or extreme working loads. These might lead to catastrophic failures that may happen suddenly.Image histogram features have been utilized for fault detection of rotating machines. The author presented the SVM based classification technique for fault detection in rotating machines [25]. The researcher presented 2D-DWT for the decomposition of thermal image [26].

4. Infrared Thermography as a Fault Diagnostic tool

IRT is a technique that is very helpful in identifying any abnormal heat pattern or inefficiencies within a machine by utilizing the thermal images for capturing IR radiations which further indicates a fault in the machine. The principle of IRT is based on the physical phenomenon that, an object having a temperature above absolute zero will emits energy having a wavelength equivalent to its temperature, and this energy is then converted to the thermal image of that object through highly sensitive IR cameras. IRT is a non-invasive and contactless technique which is competent to display real time-temperature distribution.

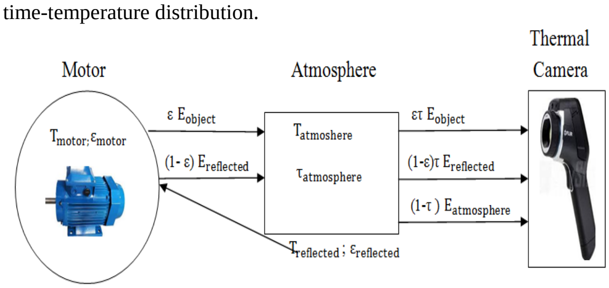


Fig. 3- Various components of thermal energy among motor and thermal camera

Fig.3 shows the heat transfer between an IM and a thermal camera. The energy received by the thermal camera comprises of energy emitted by the motor along with the energy which is reflected by surrounding as well as intercepted by the motor.

$$E_{measured} = E_{emitted} + E_{reflected} + E_{atmosphhere}$$

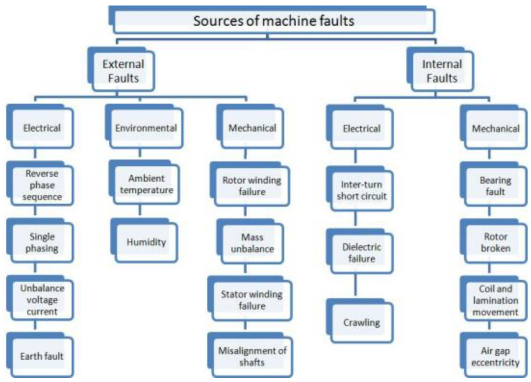
These three parameters can be calculated through Stefan's Boltzmann law. To calculate the thermal radiation emitted by the motor we need to first calculate the reflected energy. For the calculation of reflected energy, reflected temperature needs to be calculated which further is assumed to be the same for all reflecting surfaces. Keeping in mind the Kirchhoff's law it is assumed that the emissivity of the surrounding is equal to one. The total energy which is received by the motor can be communicated in the form of motor thermal energy as:

$$E_{motor} = \frac{1}{\varepsilon\tau} E_{total} - \frac{1-\varepsilon}{\varepsilon} E_{reflected} - \frac{1-\tau}{\varepsilon\tau} E_{atmosphere}$$

5. Induction Motor Faults

The major components of IM are stator, rotor, and bearings. Any damage in these components or their subcomponents will lead to the failure of IM. Usually, the IM faults are categorized as the stator, bearing, rotor, and other mechanical faults but the broad classification of IM faults is summarized in Fig.4.

Fig. 4- Classification of faults in induction motor.



Although IM is quite consistent in operation, failure in it prevents the smoothing running of IM which costs a lot to the industries. Fig.5 represents the statistical studies of IM faults by the Electric Power Research Institute (EPRI) and Institution of Electrical and Electronics Engineers (IEEE). The comparison of various faults that usually occur in rotating machines is shown in the form of a bar chart in Fig.5. These faults are categorized as bearing, stator, rotor, and other faults. The bar chart clearly depicts the frequency of their occurrence in terms of percentage. Most of the faults in rotating machines are because of the bearing failure only and covers the maximum percentage of the bar chart as shown in Fig.5.

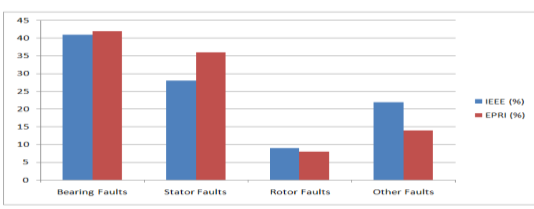


Fig.5- Study of induction motor faults by IEEE and EPRI.

5.1 Bearing Faults

Bearings are considered as one of the most significant parts of rotating machinery with a broad variety of engineering applications such as turbines, heavy machines, rolling mills, ships, etc. Bearing as the main component of the rotating machine also has certain functions as it helps in reducing the friction among the relative moving parts and in addition to that it also provides support to the rotating shaft [27]. According to IEEE and EPRI, the percentage of occurrence of bearing fault during operation is 41% and 42% as shown in Fig.5. Acoustic emission and vibration signal analysis were compared for the CM of bearings in IM [28]. The bearings defects are classified as inner race, outer race as shown in Fig. 6

Fig. 6- Bearing defects

5.2 Stator Fault

Stator winding failure is one of the most well-known faults occurring in IM [29]. Malfunctioning of IM may decrease the rate of production or it might lead to shutting down the plant, which may increase the number of accidents in the plant. Early fault diagnosis reduces the production time loss, improves the safety of the operator, and minimizes the maintenance cost [30]. Stator winding, stator frame, winding laminations, are some of the faults that usually occurs in the stator but stator windings are the most common among them. The stator winding faults are classified as coil to coil, turn to turn, phase to phase, phase to earth, and open circuit fault as discussed in Fig.7

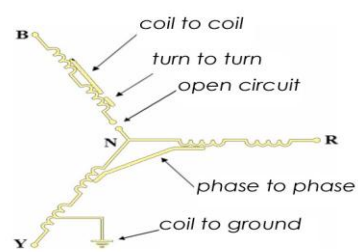


Fig.7- Stator Winding Faults

The stresses responsible for the stator winding failure are thermal, mechanical, electrical, and environmental [31]. Out of these, thermal stress plays a crucial role in the deterioration of the insulation. According to IEEE and EPRI, the percentage of occurrence of stator winding fault is 28% and 36 % as shown in Fig.5.

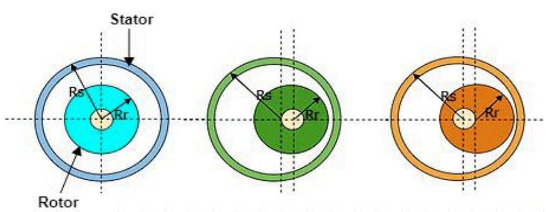
5.3 Rotor Fault

The moving component of an electromagnetic system in the IM is termed as a rotor. The squirrel cage rotor comprises of laminated steel in the core with aluminium or copper bars which are evenly distributed and are joined with a ring at either end [32]. BRB is the most common mode of failure in the rotor. In comparison to the stator winding the rotor of IM is subjected to very low voltage and much higher temperature which becomes the root cause of rotor failure. The researchers have utilized a novel methodology that is based on SVD as well as information entropy for the diagnosis of BRB and BF in IM [33]. According to IEEE and EPRI, the percentage of occurrence of rotor fault in IM is 9% and 8%

respectively. The BRB occurs due to thermal unbalance, frequent start at rated voltage, electromagnetic force, and fabricated faults [34].

5.4 Eccentricity fault

If the distance among the rotor as well as the stator in the air-gap is not uniform, the condition is termed as air-gap eccentricity. The static and dynamic eccentricity are the two categories of eccentricity faults as shown in Fig.8. If the offset between the center of the shaft and center of the stator is constant it becomes the condition of static eccentricity whereas on the contrary if the offset among the center of the shaft and center of the stator is variable it can be referred as the condition of dynamic eccentricity. R_r is the radius of the rotor and R_s is the radius of the stator as shown in Fig.8. For the identification of eccentricity faults in IM the methods like FFT, wavelet, and Hilbert transform has been used for the extraction of signals [35].



(a) (b) (c)

Fig.8- Cross-section of induction motor (a) normal (b) static eccentricity (c) dynamic eccentricity

6. Machine learning (ML) techniques

The addition of human intelligence along with machine learning is a smart approach for predictive maintenance in the electrical machine and their equipment. The common techniques which enhance the performance of CM are ANN, FL, ANFIS, SVM.

6.1 Artificial neural network

In the CM of IM, ANN emerges to be a current development. For the prediction of the remaining life of rotating machines in an accurate way, ANN has become a very powerful tool [36]. For the gathering of big data, the machine learning techniques become more suitable as it draws the outcomes about the health or current state of rotating machines. For the fault detection of BF in the rotating machines, the machine learning techniques such as ANN [37] and SVM [38] proves to be very effective techniques. For the CM of rotating machines, the various researchers have presented techniques like qualitative simulation, qualitative reasoning, etc.

6.2 Fuzzy logic:

For the optimization of preventive or time-based maintenance prioritization under the major constraints, FL has been introduced. For the traditional evaluations like yes or no and true or false, FL is a multivalued logic computational technique. Researchers have also focussed on the application of computational intelligence methods for the CM of rotating machines [39]. The truth values of variables in FL can be any real number between 0 and 1 including both. The concept of partial truth is handled by FL and the range of true value lies among totally true and totally false. To represent the vagueness and imprecise information fuzzy models or fuzzy sets are used and hence termed as fuzzy. The data or any information which is indistinct and have uncertainty is easily recognized, manipulated, and interpreted by these fuzzy models.

6.3 Adaptive neuro fuzzy inference system:

ANFIS was first introduced in the year 1990 [40]. It integrates both the fuzzy logic and neural network principles and possesses the advantages of both in the same structure. The ANFIS signifies a set of fuzzy if-then rules which contain the learning capacity to estimate non-linear functions [41]. The structural design of ANFIS comprises of five different layers. The input values are taken by the first layer which determines the membership functions belonging to them. This layer is commonly termed as the fuzzification layer. The premise parameter namely {a,b,c} is used for the computation of the membership degree of each function. The responsibility of the second layer is to generate the firing strength for the rules and is termed as a rule layer. For the normalization of computed firing strengths the third layer is used. These normalized values are taken as an input by the fourth layer. The defuzzification values are returned by this layer and these values are used by the last layer for the final output.

6.4 Support vector machine:

For the two-group classification problems, a machine learning model known as SVM is used. SVM uses classification algorithms for solving classification problems. For regression challenges as well as for classification, SVM can be used as a supervised learning algorithm [42]. In comparison to other machine learning techniques SVM is more effective as compared to other ML techniques for the fault detection of BF [43]. The accuracy of SVM is higher in comparison to other ML techniques, because of risk depreciation SVM becomes more effective than ANN. The researchers presented the PCA and LS-SVM models for the prediction of the bearing degradation process [44].

7. Deep learning (DL) techniques

DL is a subpart of ML methods that depends on neural networks with feature learning which can be unsupervised or supervised. The various deep learning techniques are CNN, auto-encoders, DBN.

7.1 Convolutional neural network (CNN)

The first paper which employed CNN for the identification for BF was published in 2014 [45]. Various researchers [46] in the past three years have used CNN for BF detection. The structure and design of CNN for fault diagnosis is shown in Fig.9. The accelerometers provide 1-D temporal raw data which further is converted to 2-D vector form. For the feature extraction, the data needs to be passed through the convolutional and pooling layer. To deepen the network the combination of the convolutional-pooling pattern needs a few repetitions. The result thus obtained is then transferred to the softmax classifier to determine the BF.

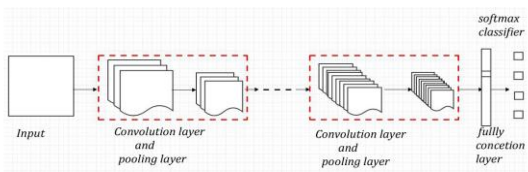


Fig.9-Structure of CNN

7.2 Auto-encoders

A pre-training technique for ANN named as auto-encoder was proposed in the year 1980 [47]. Further, it was adopted as a layer by layer neural network and feature learning method. Fig.10 shows the structure and process of auto-encoder which consists of two parts, one of them is known as the encoder and the other one is named as the decoder. The encoder output is fed into the decoder as input. Further training of ANN is done in which only the encoder part is set aside whose output will be used in subsequent stage classifier.

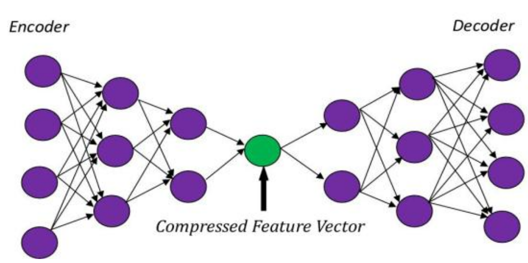


Fig 10.-Auto Encoder

In [48] a five-layer auto-encoder-based DNN was used for feature extraction which has a very high classification accuracy of 99.6% in comparison to BPNN whose accuracy is nearly 70%. Since the traditional auto-encoder doesn't possess good denoising potential in comparison to CNN, therefore researchers have implemented SDA which has a well-known and better denoising potential [49].

7.3 Deep belief network (DBN)

DBN is a neural network technique which comprises of numerous layers of hidden units as shown in Fig.11. These numerous layers have a connection among them but the hidden units in each layer don't have any connection between them. RBM is a unidirected graphical model and is the main building block of DBN having connections only between input and hidden layers. DBN has a good capability of learning features which are attained by layer by layer learning strategies.

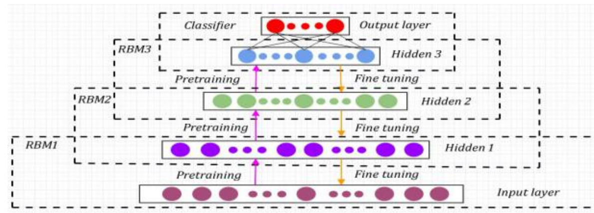


Fig.11- Architecture of DBN

7.4 Research gaps and future research

Artificial intelligence has an immense future which requires more consideration particularly in the area of DL. A hybrid DL approach can be developed which can enhance the performance of fault diagnosis and prognosis of rotating machines. The present system depends more on the collection of data, extraction of features, as well as their selection but DL techniques have the capability to build an entire package that is smart enough for real-time applications.

8. Conclusion

This paper presents the examination of various faults in IM. By comprehensive study, it turns out to be extremely clear that IRT can be used as a complimentary CM method for fault diagnosis and prognosis of rotating machines. IRT has overcome the drawback of mounting the sensors on the machines as IRT is a non-contact, non-invasive CM technique. In comparison to other non-invasive techniques, IRT is an efficiaous tool for online monitoring of IM with no human interference. The use of ML and DL techniques has improved the performance of fault diagnosis but more work needs to be done in the field of DL

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