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Remote Fault Diagnosis System Based on the Pattern Recognition and Cloud

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Abstract

This article presents a new remote fault diagnosis and alarm architecture with the use of Cyber-physical systems and Cloud technology. Due to the large quantity of data collected from machines and their processing Cloud computing and Cyber-physical systems play a key role in such maintenance purposes. Currently, several remote diagnosis troubleshooters with different diagnostic tools and connection techniques have been proposed, but they rarely find interpretable diagnosis techniques. As such, the purpose of this paper is to propose a cyber-remote fault diagnosis system based on the combination between pattern recognition techniques and Cloud Technologies. The new troubleshooter is based on Cloud Computing to connect the system components achieving the cyber-physical system definition for Industry 4.0. Our system is a remote online device that measures vibration signals. The proposed troubleshooter is tested using the run-to-failure of aerospace rolling element-bearing data sets. The results reveal that the proposed methodology improves diagnostic accuracy compared with the most popular methodology used in other related systems. Finally, current and future Cyber-physical systems and Cloud technologies applications in the maintenance field are discussed.

Keywords
Remote Fault Diagnosis System (RFDS) - Logical Analysis of Data (LAD)- Cyber-Physical System (CPS)- Pattern Recognition - Industry 4.0 - Cloud Computing

1. Introduction
Due to the new generation of telecommunication, the industry progressed to a new age (Kagermann et al. 2016). Maintenance of technical facilities and systems in operational condition is one of the most crucial factors in assuring their high availability and reliability [Werbińska 2023]. Because poorly maintained equipment can result in more frequent failures of facilities and their components, poor operational efficiency, or delays in achieving operational schedules, maintenance has increasingly attracted the attention of engineers and management. Poorly chosen or planned maintenance strategies for any equipment can lead to, among other things, receiving items of dubious quality, lowering energy efficiency in some sectors, or under/over-utilizing maintenance staff (Kumar 2000, Crespo et al. 2018). As a result, an increasing number of businesses are making efforts to boost the effectiveness of the maintenance process for their physical assets [Kagermann et al. 2016 to Crespo et al. 2018]. New technologies such as Cloud computing makes communication between the maintenance process. Also using the data mining techniques gives the ability of generates interpretable patterns which illustrate the hidden phenomena of the machine condition.

In the following section, the objectives of the research are illustrated to focus on the unique Remote Diagnosis System (RDS). The new RDS uses the cloud to communicate between the maintenance layers and data mining techniques to transfer the raw vibration signals collected from the monitored machines to a decision rule [Ragab et al.2016]. Figure (1) illustrates the RDS layers.

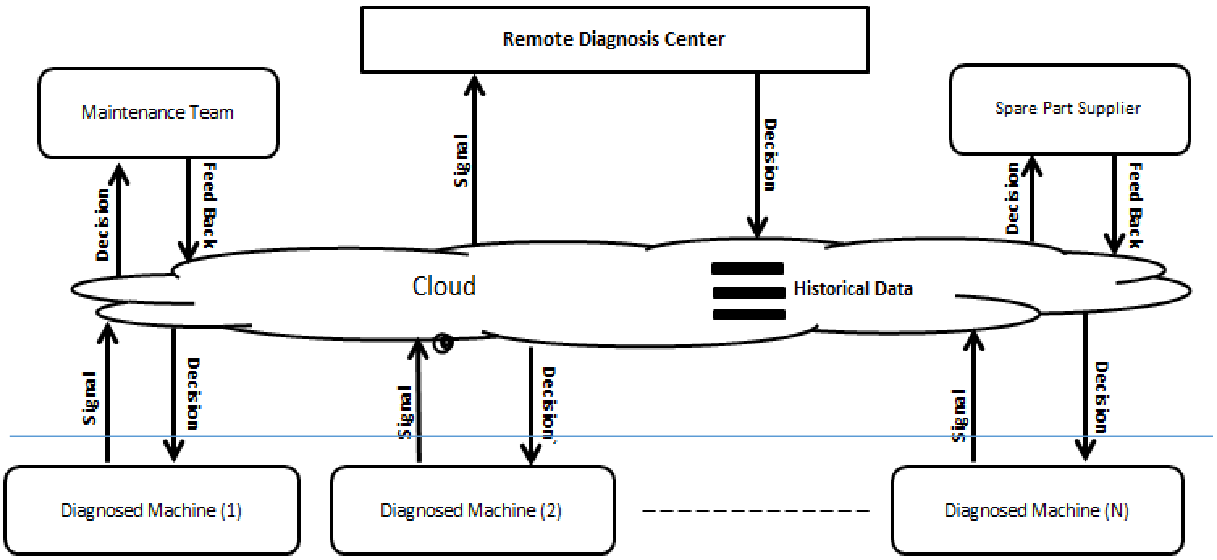

Figure 1. RDS Layers.

1.1 Objectives
The originality arises from the use of a combination between the supervised machine learning and cloud computing platform for build a unique troubleshooter which use for the diagnosis of the machine's operating behavior. The new RDS transfers the labeled data to generate an interpretable decision rule to be used in the supervised maintenance process.

2. Literature Review
Many of the popular remote diagnosis and decision-making troubleshooter has been applied already for the smart troubleshooter to diagnose and makes the corrected decision to keep the monitored components performed in a healthy condition. For example, Almobarek et al. 2023 built a framework based on the industry survey study outcomes and divided it into three parts: setup, machine learning, and quality control. Ali et al. (2020) propose a cloud computing platform consisting of three layers of techniques forming a Cyber-Physical system. Li et al. (2021) proposed a novel fault diagnosis model by combining binarized DNNS with improved random forests (RFS). The most crucial literature papers relating to the evolution of maintenance in Industry 4.0 was presented by Nardo et al. (2022). Huang et al. (2022) proposed a deep residual networks-based IFD method of planetary gearboxes in cloud environments. A cloud-based IFD design is proposed to use the supercomputing power of cloud computing to solve the related issues caused by the insufficient computing power of local equipment. Menegonet et al. (2023) comprises a literature review undertaken to identify the multiple types of Digital twins' models, examine barriers and opportunities associated with their use, and discuss their potential as enablers of inspection and maintenance strategies. Liang et al. (2023) proposed a small sample rotating machinery fault diagnosis method based on a multi-branch and multi-scale dynamic convolutional network (MBSDCN). New Smart Warning System (SWS) implemented by Ali et al. (2021) use to send a warning-level report about the machine component's failure behavior via distance is proposed in this article.

Based on the former literature survey the aim of this study arises to build a remote diagnosis troubleshooter by using the combination of data mining technique and cloud computing to receive a labeled vibration signal and generate interpretable patterns to be used in maintenance decision-making. The combination of the new technologies brings the proposed RDS to a new age of industry.

3. Methods

In the industrial field, there are several types of generated data that implement the operation behavior of the mechanical parts. The popular signals can be thermal imaging, vibration signal, and oil particle signal (Li et al. 2021). Many researchers present the fault characterization for rotating machines using the vibration signal to show the behavior of the operation condition of the monitored equipment. The first step in the proposed methodology is feature extraction. In the feature extraction step the raw vibration signal transfers to popular statistical features which can in data mining to discover the hidden patterns which illustrate the monitored component behavior. In the following table (1) the statistical feature formula is illustrated.

Table 1. Feature formula:

Feature Name	Formula
Mean	$Mean = \frac{\sum_{i=1}^{N} y_i}{N}$
Range	$Range = Max(y_i) - Min(y_i)$
Standard Divination	$STDE = \sqrt{\frac{\sum (y_i - \bar{y})^2}{(N-1)}}$
Crest Factor	$CF = \frac{Max(y_i)}{RMS}$
Kurtosis	$Ku = \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum \left(\frac{y_i - \bar{y}}{STDED} \right)^4 - \frac{3(n-1)^2}{(n-2)(n-3)}$
Root Mean Square	$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \bar{y})^2}$
Skewness	$Sk = \frac{n}{(n-1)(n-2)} \sum \left(\frac{y_i - \bar{y}}{STDED} \right)^3$

Where N is the length of data and (y) is the amplitude of the vibration signal.

In our work, we use popular data mining techniques to discover the hidden patterns which illustrate the machine conditions. The technique used in this paper is Logical analysis of data (LAD). LAD converts the labeled data into a decision rules used to build the remote central monitor and control hub [Li et al. 2021, Qiu et al. 2006]. The generated patterns are used as a decision rule. By using the generated decision rule the RDS was built. The proposed RDS receives the vibration signal from the smart sensors and converted it to useful features. After that, the system compares the received machine conditions with the patterns generated in the offline step. The system gives the correct decision and sent it back to the local maintenance team to make the corrective maintenance task to make the machine works near zero breaks down. The proposed system decreases the maintenance cost and increases the reliability of the machines. Cloud also gives the ability to connect the proposed system and multi machines in many places at the same time.

The Architecture of the proposed system is illustrated in the figure (1). The system consists of two sides; the first side is the monitored machine side and the virtual side. On the monitored machine's side, smart sensors are installed on the monitored component to collect the raw vibration signal and send it to the virtual side. The virtual side connected to the other side by using the capability of cloud technology. Cloud gives the proposed system the ability to communicate between the maintenance process sides.

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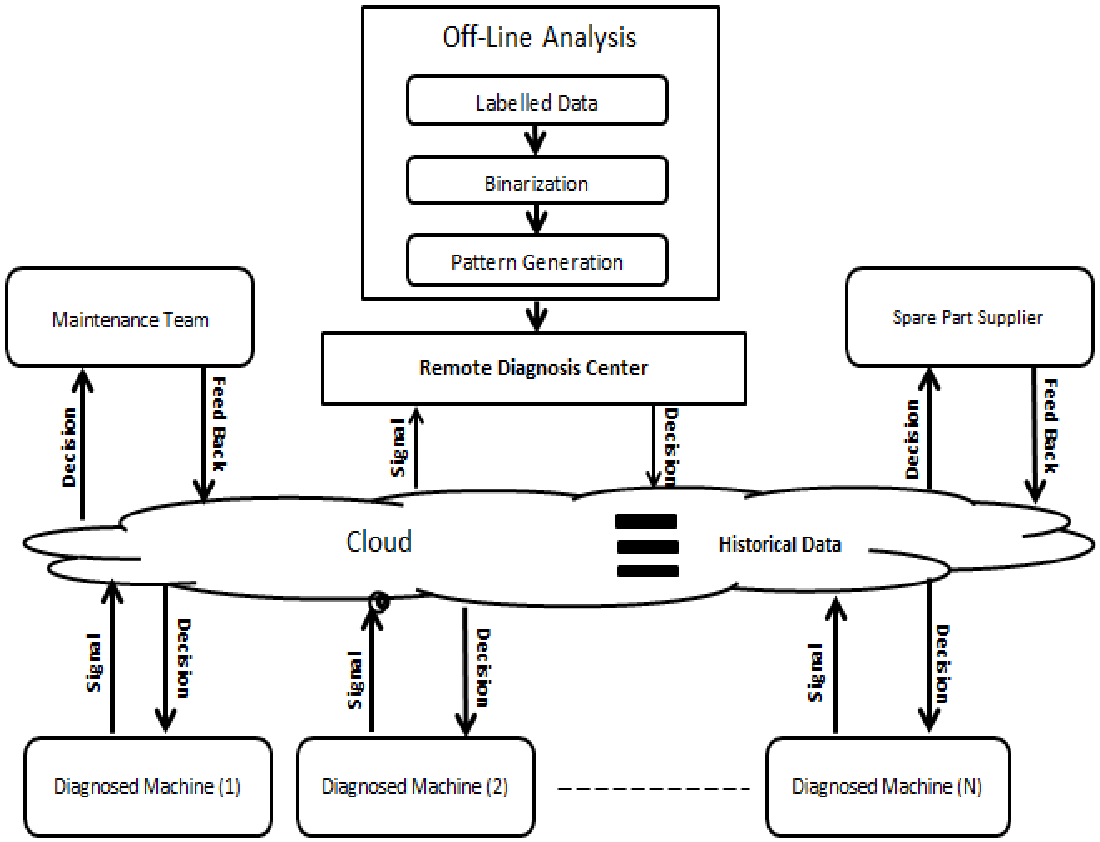

Figure 2. Architecture of Labeled Remote Diagnosis system

Figure (2) illustrates the architecture of the labeled remote maintenance system is divided into three layers; the first one is the monitored machines with smart sensors installed on top of them to record the vibration signal of the mechanical component. The smart sensors are connected to the Cloud via the internet to transfer the collected data to the Cloud. In the second layer, the collected data is stored in the Cloud and then sent to the remote diagnosis center which is the third level. In the remote diagnosis center, the decision-making process is performed by comparing the pattern in the test data with the pattern generated from the offline analysis for the historical data of the component. The continuous monitoring of the mechanical component improves the system reliability, and working hours and achieves the near zero break down. The decision is then returned to the Cloud and passed to the control model on the monitored machine to adjust the controlled variables to achieve the decision orders. Also, the decision is sent to the maintenance team to check the performance of the machine and do the necessary actions according to the decision generated from the remote maintenance. Also, the signal on which the decision based on the proposed is sent to the local maintenance team with the discovered patterns for rechecking before performing the actions. In a parallel way, if there is a need for a spare part, its specification is attached to the massage of the spare part supplier/division to prepare the necessary component to help the local maintenance team to achieve the maintenance task in the minimum time to decrease the time of maintenance.

4. Data Collection

To test the proposed system, a simulation model of a labeled cyber-physical maintenance system of rolling element bearing failure is developed. The tested data is extracted from a run-to-failure data set of signals obtained from the National Science Foundation's Industry/University Cooperative Research Centre for Intelligent Maintenance Systems (IMS) through the NASA prognostic data repository shown in Figure(4) below. The test rig setup consists of a constant speed motor (2000RPM) coupled to a shaft supported with four rolling element bearings. The four types of bearings are Rexnord ZA-2115 double-raw bearings with 16 rollers in each raw, 71.5 mm pitch diameter, 8.407 mm roller bearings, and a tapered contact angle of 15.170 (Lee et al., 2006). A high-sensitivity Quartz ICP accelerometers PCB 353B33 were installed on the bearing housing. The card was used to collect a snapshot of the vibration signal every ten minutes with 20 kHz sampled signals until a failure occurred. This test was carried out over seven days. Table (2) illustrates a sample of feature extraction using MATLAB Software. In the following table, the features are extracted from the raw vibration signal.

Table 2. A sample of the extracted labeled feature.

Class	range	Mean	SD	Skewness	Kurtosis	RMS	Crest Factor
0	0.84	-0.0102	0.0735	0.084	0.6292	0.0742	6.12
0	0.757	-0.0026	0.0753	0.0521	0.6487	0.0754	4.895
0	0.782	-0.0024	0.0784	0.0282	0.6036	0.0785	4.983
0	0.805	-0.0016	0.0783	0.0269	0.4565	0.0783	5.606
0	0.796	-0.0016	0.0786	0.0586	0.479	0.0786	4.934
1	1.015	-0.0019	0.0993	-0.1187	0.7723	0.0993	4.863
1	1.03	-0.0017	0.1028	-0.0744	0.9274	0.1028	4.748
1	0.966	-0.0019	0.1005	-0.1208	0.6657	0.1005	4.806
1	0.871	-0.0018	0.0994	-0.1102	0.7493	0.0994	4.025
1	1.021	-0.0021	0.1026	-0.07	0.8227	0.1026	4.737

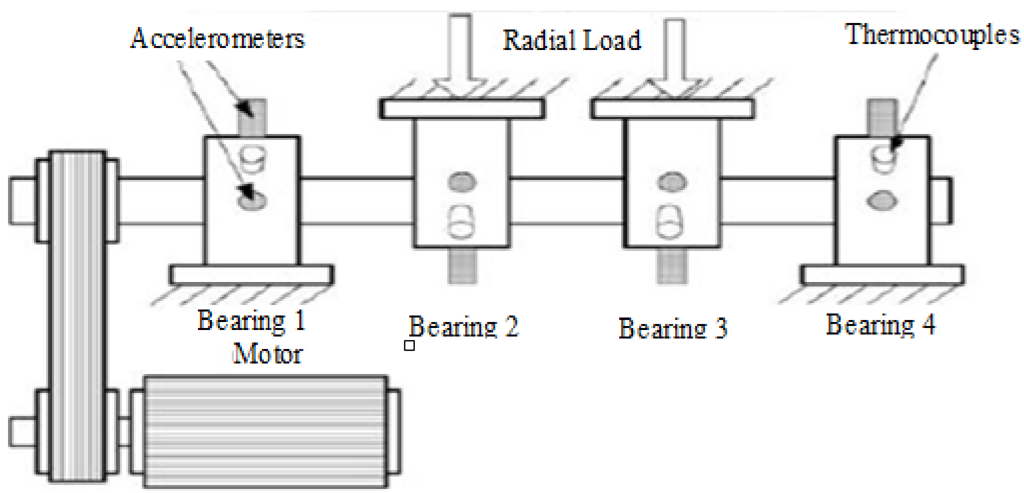

Figure 3. Bearing test rig and sensor placement illustration (Qiu et al., 2006).

5. Results and Discussion

In this section, an analysis of signal features for fault detection is presented in the time domain. The time domain features calculated from the vibration signal are descriptive statistics. The seven features used in our analysis are Range, Mean, standard divination, Skewness, Kurtosis, Root Mean Square, and Crest Factor features are illustrated in table (2) calculated by using MATLAB Software. The first step uses feature variation to find the behavior of the fault propagation. The most significant feature variation graphs are presented to discover the cut point between healthy and unhealthy cases. Figures (4, 5, and 6) present the variation of bearing behavior which can be used as a cutting point between the two cases. By using this variation, we can label the data to use the supervised LAD to find the hidden pattern of the phenomena. The cut point which divides the two cases is signal number (702). This point will be used in labeling the signal features into a healthy case for a signal number less than 702 and an unhealthy case for a signal number greater than 702.

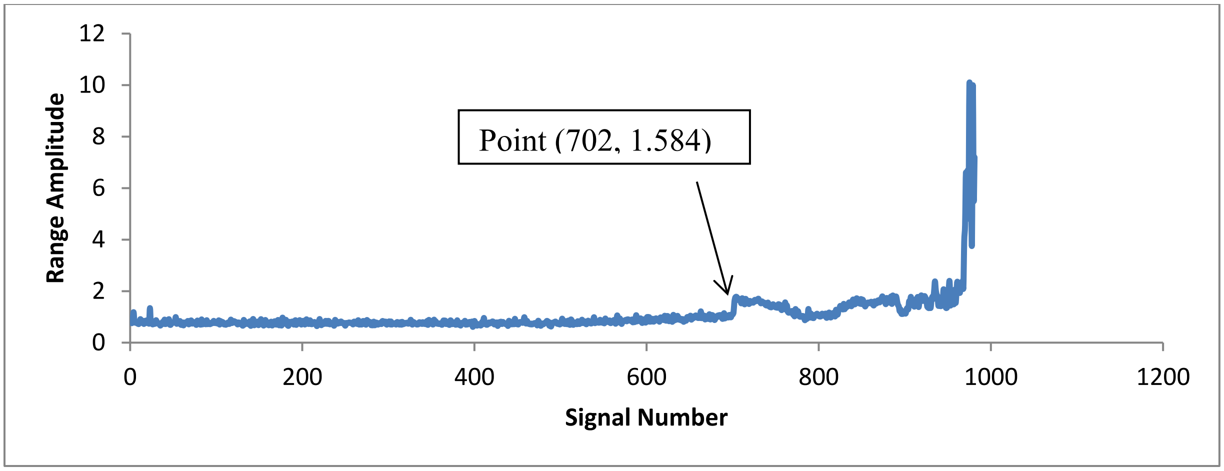

Figure 4. the range values for each signal

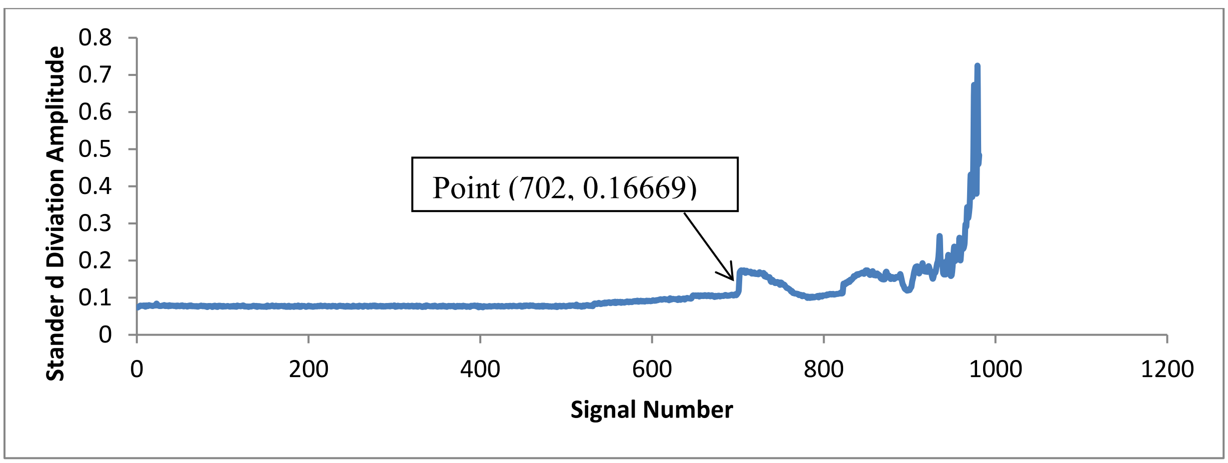

Figure 5. the standard divination values for each signal.

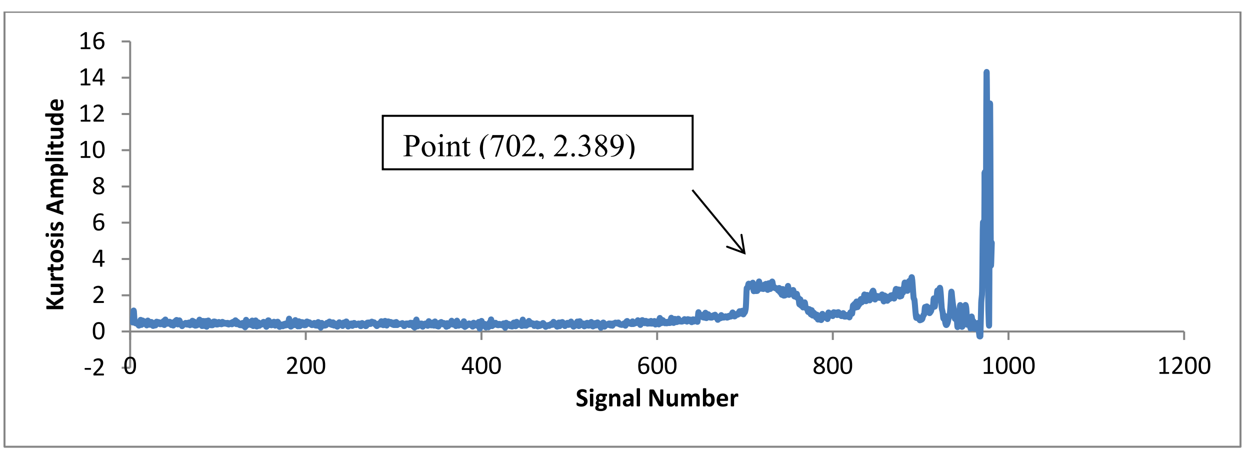

Figure 6. the kurtosis values for each signal.

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5.1 Proposed Improvements

We proposed a new technique that is not used before in remote maintenance systems. We found that the most popular machine learning techniques according to the literature survey are ANN and SVM. So we compare the proposed supervised machine learning technique and the most popular techniques. The comparison factors are the accuracy and interpretability of each technique. Table (3), the accuracy between the proposed and most popular techniques is compared. The proposed technique has the highest accuracy which improves the maintenance efficiency. On the hand, LAD beats the other technique in the second-factor interpretability. The comparison result drives the usage of LAD as a preferable technique in building the diagnosis mode. The diagnosis model is based on using the Cloud to communicate between the monitored machine and the diagnosis model to overcome the distance effect and improve the ability of real-time monitoring to achieve near-zero breakdown. Using the Cloud is matched with the requirement of the third level of Cyber-Physical Systems. The test is done by the National Science Foundation's Industry/University Cooperative Research Center for Intelligent Maintenance Systems (IMS) through the NASA Prognostic data repository. The difference in this case is that the new data set is being unlabeled; meaning that there is no class separation between the two classes. The method is proposed to convert the unlabeled data to a labeled one. The proposed method is using the feature plot to find the cut point between the different classes. The proposed method and the results are illustrated in Figures (4, 5, and 6). The architecture of the labeled remote diagnosis system is proposed in Figure (2). It solves two problems; the first one is the remote location and the second one is connecting all maintenance process partners such as the local maintenance team in the physical field near the monitored machines. Also connecting to the spare part suppliers to prepare the required spare part needs to make the maintenance process.

5.2 Validation

The following step is to validate the data to use supervised LAD to find the hidden patterns by comparing the proposed technique and the popular machine learning techniques Artificial Neural Network (ANN) and Support Vector Machine (SVM). In the following table, we compare the accuracy of ANN, SVM, and LAD for each method of labeling. Table (3) illustrates the accuracy of each Machine Learning technique.

Table 3. Average Model Accuracy of each Technique:-

Technique	ANN	SVM	LAD
Accuracy	95.001%	92.9664%	96.0396%

Table (3) illustrates that LAD has higher accuracy compared to the other techniques. So we use LAD to build the model of remote diagnosis for labeled data.

6. Conclusion

In this paper, a new remote maintenance labeled system based on LAD is developed. The proposed model is tested by using a run-to-failure data set of aerospace bearings collected from the NASA Prognostic data repository with different faults. The LAD diagnosis tool is compared with the most popular techniques ANN and SVM. The proposed technique, LAD, makes both diagnosis and decision by the involvement of the Cloud technologies to match the cyber-physical-system requirements to achieve the buzzword nowadays Industry 4.0. The advantages of the proposed system are reduced maintenance process cost by the continuous monitoring of the operating behavior of the mechanical part to achieve near zero breaks down. The reliability of the monitored machines is enhanced which improves the industry process cost. Also by using the proposed machine learning technique avoid an expensive onsite need for expert engineers visit to the machines local site of the monitored machines. The system is based on Cloud Computing technology to connect the proposed RDS layers. The proposed layers are a sensor layer, connection layer, collect analysis and decision-making layer. The analysis of collected vibration signals is constructed based on an interpretable methodology dealing with labeled data. The proposed analysis techniques are divided into three steps. The proposed steps are data collection by using smart sensors, statistical feature extractions, and graphical methods to divide the extracted data into classes. In summary, the proposed RDS helps to achieve the continuous monitoring and decision-making of the maintenance process via distance based on Cloud technology possibilities. The implemented system connects the maintenance process chain to achieve the near zero breaks down.

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In future work, the performance of the remote diagnosis system will be enhanced by improving the proposed technique. A multi-component diagnosis using the same diagnosis center will be the future step. Furthermore, enhancing the communication between the system components to increase the reliability of the maintenance task will be considered. This step will be used in the real-time learning remote maintenance system.

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