MEDICAL EQUIPMENT EFFICIENT FAILURE MANAGEMENT IN IOT ENVIRONMENT

by

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Abstract

Technological advancements are the main drivers of the healthcare industry as it has a high impact on delivering the best patient care. Recent years witnessed unprecedented growth in the number of medical equipment manufactured to aid high-quality patient care at a fast pace. With this growth of medical equipment, hospitals need to adopt optimal maintenance strategies that enhance the performance of their equipment and attempt to reduce their maintenance cost and effort. In this work, we are proposing a Predictive Maintenance (PdM) strategy that relies on real-time data by using the Internet of Things (IoT) technology to help in the diagnosis of the failure. The proposed approach involves maintenance logs analysis, criticality assessment, failure modes analysis, feature selection, and machine learning implementation. The proposed approach has to be economically feasible and efficient in terms of selecting and monitoring the right parameters that reflect the health of the equipment. The approach was demonstrated using a case study from a local hospital- Sharjah, where critical equipment of Vitros immunoassay was analyzed. The maintenance strategy was changed from corrective to predictive using wireless sensors that monitors vibration signals. Features extracted and selected are analyzed using Support Vector Machine (SVM) to detect the faulty condition. In terms of economics, our approach proved to provide significant cost savings that can reach up to 25% which is worth investing in. The approach is scalable and can be used across medical equipment in large medical centers.

Keywords: ***Medical equipment; maintenance; healthcare; failure management sensors; Internet of Things; IoT.***

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List of Abbreviations

ADC	Analog to Digital Conversion
AI	Artificial Intelligence
ANN	Artificial Neural Network
BPNN	Back-propagation Neural Networks
CBM	Condition-Based Maintenance
CAGR	Compound Annual Growth Rate
CF	Cash Flow
ECG	Electrocardiogram
FFT	Fast-Fourier Transform
FMEA	Failure Mode and Effect Analysis
GP	Gaussian Process
IDC	International Data Corporation
IoT	Internet of Things
IWPT	Improved Wavelet Package Transform
KNN	K-Nearest Neighbours
LDC	Linear Discriminant Analysis
MARR	Minimum Attractive Rate of Return
MLC	Maximum Likelihood Classification
NN	Neural Network
NPV	Net Present Value
O&M	Operations and Maintenance
PCA	Principal Component Analysis

PdM	Predictive Maintenance
P-F	Potential Failure
PM	Preventive Maintenance
RCM	Reliability Centered Maintenance
RMS	Root-Mean-Square
RPN	Risk Priority Number
RTF	Run-to-Failure
RTM1	Real-time Monitoring
RUL	Remaining Useful Lifetime
SVM	Support Vector Machine
VAT	Value- Added Tax
WSN	Wireless Sensor Network

Chapter 1. Introduction

In this chapter, a short introduction about maintenance strategies, IoT, and classification methods will be provided. Furthermore, the problem statement, thesis objectives, research contribution, and thesis organization will be discussed.

1.1. Overview

The healthcare industry in general and hospitals, in particular, are considered to be of unique and complex systems because of the group they serve. Since this industry is dealing with human beings, hospitals consider personal safety as a priority that must be satisfied before anything else. For this purpose, the healthcare industry is always trying to improve the systems, minimize risks, and use the latest technology devices. But unfortunately, in some cases, this development of devices is creating more complex systems which in turn are increasing the cost of maintenance. This is the point where the selection of an appropriate maintenance management strategy becomes very critical and useful especially considering the limited budgets and the need to strike a balance between maintenance costs and level of services [1].

1.2. Maintenance

Maintenance can be defined as a combination of technical and managerial actions that are essential to maintain and restore equipment in the optimum operating condition by increasing their reliability and availability and reducing their failure rate [2]. The maintenance of devices involves testing and maintaining them or replacing any part if necessary. The effective management of this process ensures the high quality of device performance, which reflects on the accuracy of the readings and the safety of end-users [3]. In addition to that, maintenance management will have a great impact on the functionality of the components by extending their useful lifetime, hence reducing the cost of maintenance [4].

1.3. Reliability Centered Maintenance (RCM)

It is the process of selecting the most suitable and appropriate maintenance strategy. This philosophy aims to increase the functionality and availability [5] of the components over their life cycles with the use of least maintenance actions [6].

RCM includes the following strategies: Preventive Maintenance (PM), Predictive Maintenance (PdM), Real-time Monitoring (RTM1), and Run-to-Failure

(RTF- also called reactive maintenance). For a better understanding of the RCM, we need to understand the meaning of failure. Failure in simple words is a condition in which the equipment is not able to accomplish and achieve the required output. The consequences of failure will have an impact on determining the appropriate maintenance strategy as well as improving the system to minimize the occurrence of failures [7]. The outcomes of the RCM analysis [8] are shown in Figure 1.

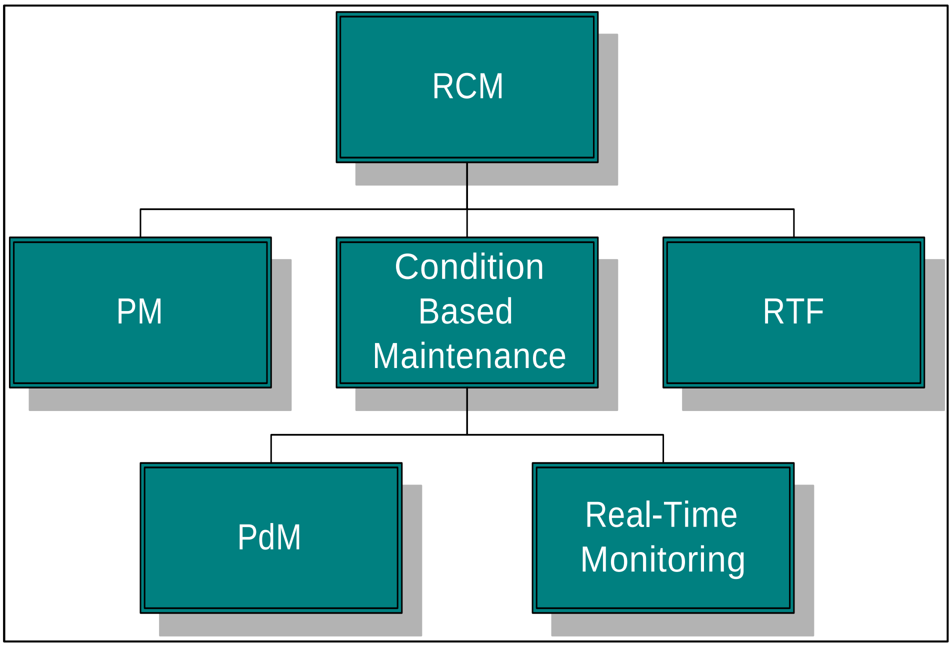

Figure 1: RCM elements [7].

1.3.1. Preventive maintenance. It is the most commonly applied and implemented where it is performed regularly after a scheduled time or a certain amount of usage while the device is still working, regardless of the equipment condition [6]. PM is also referred to as time-driven or interval-based maintenance.

This strategy was introduced after the corrective (RTF) strategy in order to reduce the failure occurrence [9] and extend the lifetime of the device/ system, even though searches and studies nowadays are showing that this strategy is being costly in the long term since it is not taking into account the current status of the device and it is being performed even if the device is working properly and in good condition [10].

The following are some advantages of the PM over the RTF [11]:

- The ability to plan for the maintenance action and perform it at a suitable time.
- Reduce the cost of maintenance by reducing the downtime.
- Improve the safety of patients.

However, the PM has some disadvantages that need to be reduced [12]:

- Ignoring the status and condition of the equipment, resulting in performing unnecessary tasks.
- Human errors are making the condition of the equipment worse.
- Increased costs due to the use of spare parts and labor.

1.3.2. Condition-based maintenance. This strategy is performed when one or more indicators show that the equipment is about to fail, or its performance is dropping down. The main aim of the CBM is to take advantage of the information extracted regarding the equipment degradation, and with the help of the sensors, breakdown times of the equipment can be minimized [13].

1.3.3. Predictive maintenance. This strategy predicts when the failure of the equipment might occur and prevents this occurrence by performing maintenance action at the right time. As mentioned before, if certain indicators reach the threshold point, engineers will have to take action. Noise, vibration, temperature, and pressure are some physical measurements that can indicate the condition of the equipment.

By monitoring the future state of the equipment, the maintenance actions will be scheduled and planned properly. Compared to PM, PdM is performed only when the need for maintenance arises, not based on a certain time passage or a certain usage [14].

Applying this strategy will reduce the times' maintenance actions are performed like in preventive maintenance because of the ability to detect the failure in early stages, which in turn minimizes the cost wasted on the use of more spare parts.

Figure 2 describes the concept of PdM. It illustrates the relationship between the time where the failure starts to occur, and the cost as the time passes and more indicators start to warn the user.

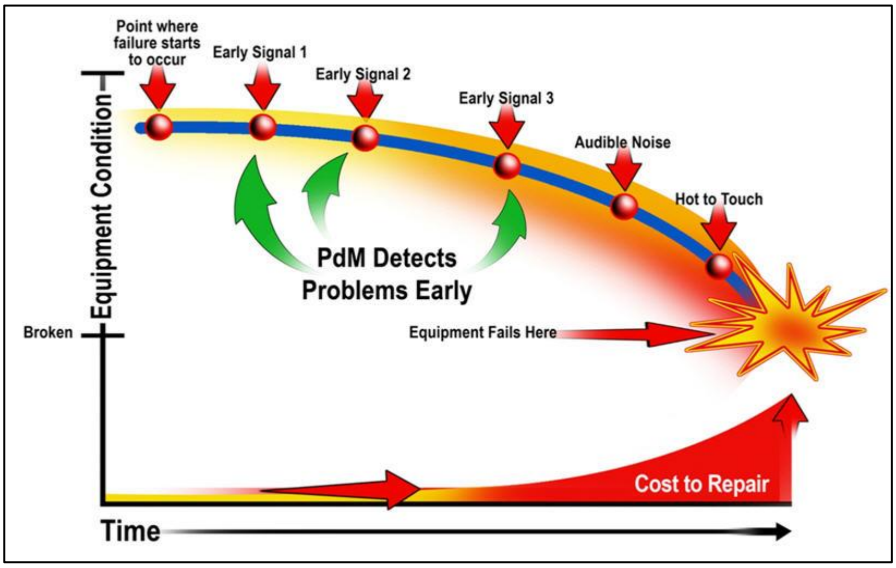

Figure 2: PdM concept [15].

The equipment usually starts to break down and fail gradually. It will give off several warnings that will be detected by the sensors. This will give the user enough time to schedule the maintenance action before reaching the breakdown point. The longer the time, the higher the cost that will be spent on repairing the equipment. Potential Failure (P-F) curve is shown in Figure 3. It is an important tool that can be used in the RCM program to extend the lifecycle of the equipment.

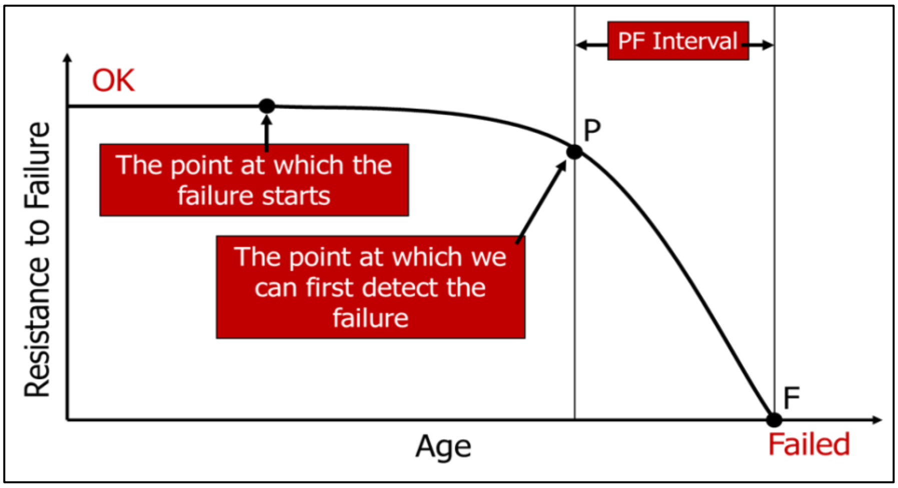

Figure 3: Potential Failure (P-F) curve [15].

Using such a tool will help in detecting early failure signals which are difficult to be discovered without the use of such tools. Besides, it will help in selecting the best maintenance strategy for a certain case based on the signals of failure that we are getting from the equipment.

For example, if the indicator of the oil is giving a warning signal, then the PdM can be applied, but if the equipment starts to heat up and produces noise then we must consider the RTF strategy as shown in Figure 4.

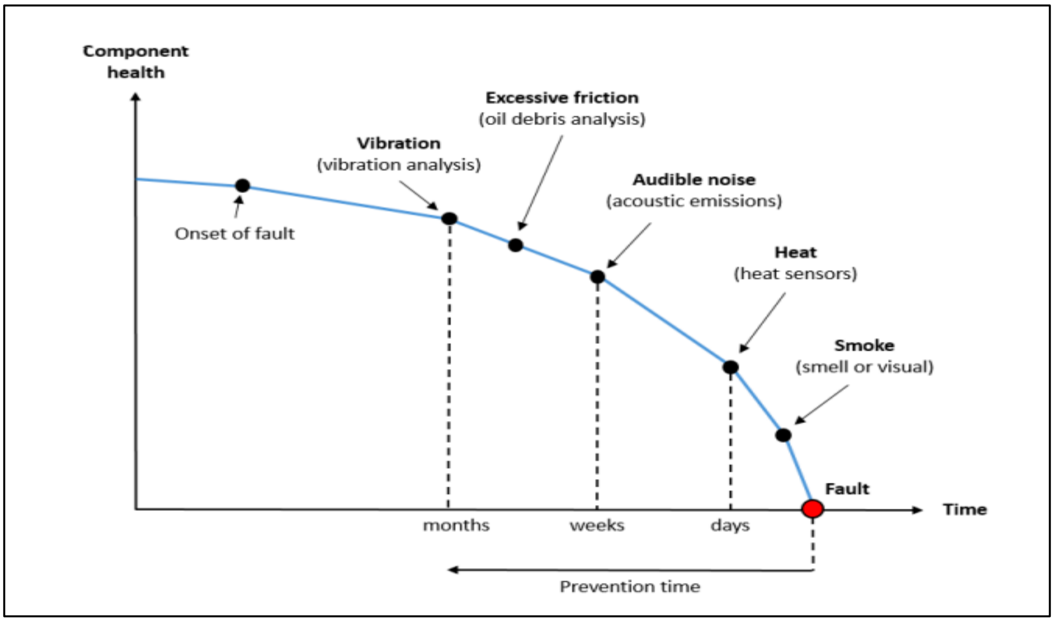

Figure 4: P-F curve [16].

1.3.4. Run-to-Failure (RTF) maintenance. It is the oldest strategy and performed after the failure of the component or system. In simple words, only when the component is broken, then it will be fixed [2], [17], [18], [19]. It is also called the corrective or reactive strategy. The aim of using this strategy is to restore the functionality or operation of the broken part [10]. Generally speaking, in some cases this strategy may require less planning than the PM, but unexpected failure means that spare parts may not be readily available, causing the hospital to pay more for emergency parts shipping [2]. Moreover, depending on this strategy will lead the equipment to work in improper conditions sometimes, which results in higher consumption of energy [20]. In terms of maintenance costs, studies have shown that repair using this strategy costs three times a repair action using scheduled or PM [2], [14].

1.4. Internet of Things (IoT)

IoT is a concept reflecting a connected set of anyone, anything, anytime, anyplace, any service, and any network [21]. Nowadays, using IoT technology is rapidly growing in different industries such as healthcare, environment, supply chain, and logistics [22].

In the coming years, the number of connected devices to the internet is expected to increase sharply. By 2020, the number is estimated to reach 26 times people [23].

One of the areas of utilizing IoT is to use it in monitoring which can be achieved by having wired or wireless sensor networks which comprise of thousands of inexpensive sensors that can report their values to the cloud servers, to ensure safety, efficiency, and better decision making [24]. One advantage of using the cloud is the ability to share the information which will help in understanding the complete picture of the system and therefore manage the hidden risks [25].

In terms of architecture, there is no single architecture agreed globally, but the basic one is composed of three layers as illustrated in Figure 5 which are: Perception layer, Network layer, and Application layer.

The perception layer or the sensing layer represents the physical layer that involves the use of different sensing technologies (e.g., RFID, NFC, GPS) to collect data of different parameters from a certain object or environment. It can also involve converting the data into the digital form using some microchips which are capable of doing the Analog to Digital Conversion (ADC). The network layer is responsible for transmitting the data from the sensors to the application layer. In the application layer, data will be received by the central system/ smart devices and servers. Then it will be used in various applications that provide different services for the users, including the ability to monitor the changes in the status of the sensors and therefore helping in taking an accurate decision [26], [27].

1.5. Classification

Classification using machine learning tools can be very useful in terms of data modeling and analysis. In this section, multiple tools that will be used later in our work are discussed.

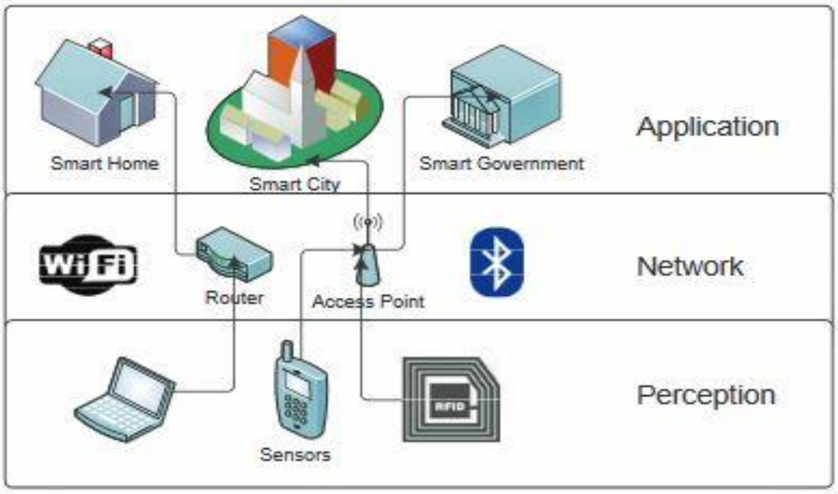

Figure 5: Three-layer IoT architecture [15].

1.5.1. Principal component analysis (PCA). This tool is one of the oldest statistical procedures that involves reducing the dimensionality of datasets to increase interpretability while reducing the loss of information. The working mechanism of this tool is based on creating uncorrelated variables, the principal components, which are linear functions of the original variables to maximize the variance [28].

We begin by finding the adjusted matrix, X, which is constructed from n observations (rows) and p variables (columns). The adjustment is made by subtracting the variable's mean from each value. That is, the mean of each variable is subtracted from all of that variable's values.

The principal components are constructed as weighted averages of the original variables. The specific values of a specific row of the principal components can be referred to as scores. The matrix of scores will be referred to as matrix Y. The basic equation of PCA is, in matrix notation, given by Equation (1):

$$Y = W'X \tag{1}$$

where W' is a matrix of coefficients that are determined by PCA.

1.5.2. Support vector machine (SVM). This machine learning algorithm is used for data classification [16]. The working concept of this algorithm involves plotting every single data point in an n-dimensional space, where n represents the number of features that can be used to train the model.

The purpose of classification can be achieved by finding the hyperplane that classifies data. Figure 6 illustrates the idea of SVM. The margin which is displayed in Figure 6 is considered to be the distance between the hyperplane and the nearest data point for each class.

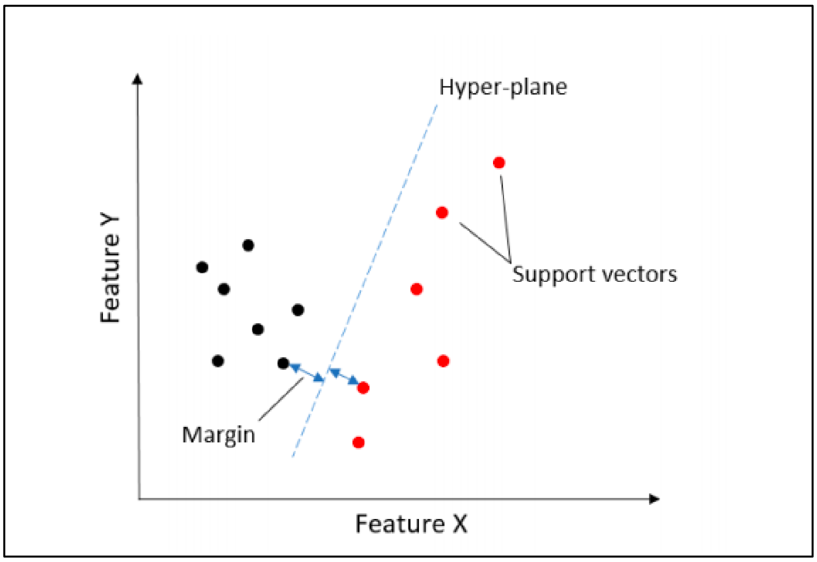

Figure 6: SVM classification [16].

Based on previous work and since we will be having two classes, healthy and faulty, we will use this model in MATLAB. The mathematical formulation involves the use of a training set (x_i, y_i) where i =1,2,3……, l, $x_i \in R^n$, the class label $y_i \in \{+1, -1\}$ which is either positive or negative, n is the number of features and l is the number of training data points. The SVM approach aims to construct a classifier in the form of Equation (2) [29]:

$$y(x) = \mathrm{sign}[\sum_{I=1}^{N} \alpha_i \, y_i k(x, x_i) + b] \tag{2}$$

where α_i are positive real constants, b is a real constant, and $k(x, x_i)$ is the kernel function.

For $k(.,.)$ one typically has the following choices: $k(x, x_i) = x_i^T x$ (linear SVM); $k(x, x_i) = (x_i^T x + 1)^{\,d}$ (polynomial SVM of degree d); $k(x, x_i) = e^{\left\| -\frac{x - x_i}{2\sigma^2} \right\|^{2}}$ (Gaussian SVM) where σ is the width of the kernel.

1.5.3. Decision trees. Decision tree methodology is one of the most powerful and popular machine learning algorithms used for data classification for developing prediction algorithms for a target variable [30]. This method classifies a dataset into branch-like subsets that build an inverted tree with a root node, internal nodes, and external nodes. This algorithm is capable of dealing with large and complicated datasets without creating a complicated parametric structure. Considering a large sample size allows the data to be divided into training and validation datasets. The optimal final model can be figured out by training datasets to build the tree model and use a validation dataset to help in deciding on the size of the tree.

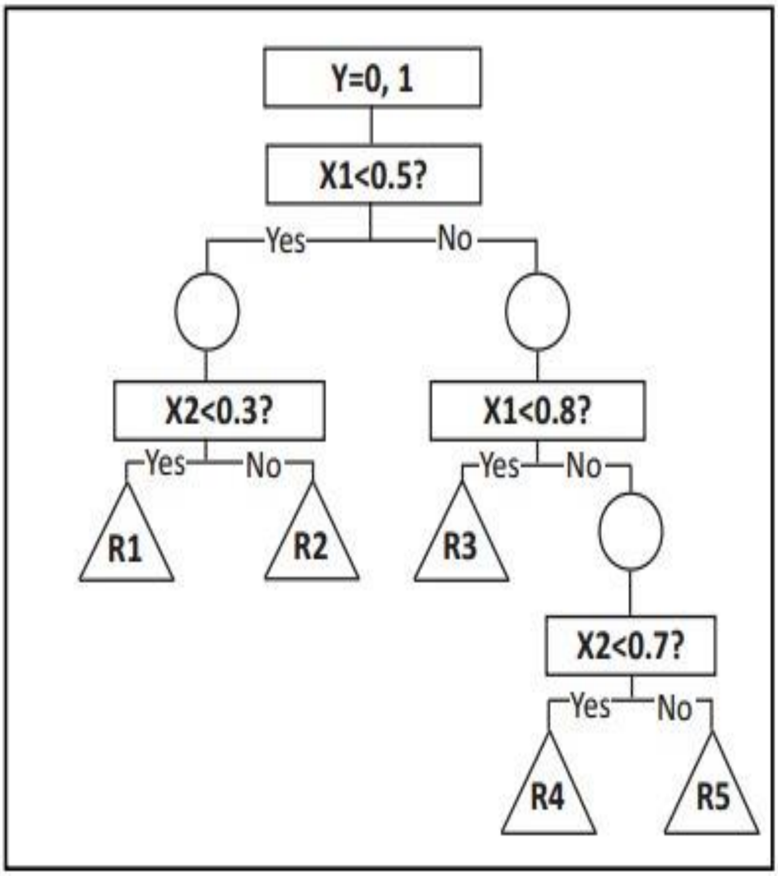

Figure 7: Example of a decision tree [30].

For building the decision tree, one of the input variables at each step will be chosen to split the samples. According to the selected variable, the split point will be determined by an attribute value test.

The most commonly used measures for the decision classification trees are entropy which can be calculated from Equation (3) and Gini impurity that can be calculated from Equation (4):

$$H_e(S) = -\sum p(y) log\, p(y) \tag{3}$$

$$H_g(S) = -\sum p(y)\big(1 - p(y)\big) = 1 - \sum p(y)^2 \tag{4}$$

where *S* represents the dataset, and *p(y)* is the proportion of the number of samples with the class label.

1.6. Validation

Validation is the process of assuring that the model can get the patterns of the data correctly and being low on bias and variance. Bias measures how much the expected value varies from the correct value θ. While the variance measures how much the data is varying around the expected value. Bias can be estimated using Equation (5):

$$b_\theta(d) = E[d(x)] - \theta \tag{5}$$

where $d(x)$ is the estimator of θ. And variance can be estimated using Equation (6):

$$var(d) = E[(d - E[d])^{\,2}] \tag{6}$$

In other words, it checks if the hypothesized relationships between variables are being accepted to describe a certain set of data. In our work, two types of validation were tested, holdout validation and K-fold cross-validation.

In holdout validation, a part of the training data is being removed aside so that it can be used to get predictions from the model trained on the rest of the data. While in K-fold cross-validation, the dataset is divided into k-folds, and then the holdout method can be applied and repeated k times such that one k-fold is used as a test set for each time and the other k-1 folds form the training dataset. The choice of k is usually 5 or 10, but there is no formal rule [31]. Figure 8 illustrates the schematic diagram of both holdout validation and k-fold cross-validation.

After performing the validation and training the models, the resulted confusion matrices will be describing the accuracy, sensitivity, and specificity of each classifier.

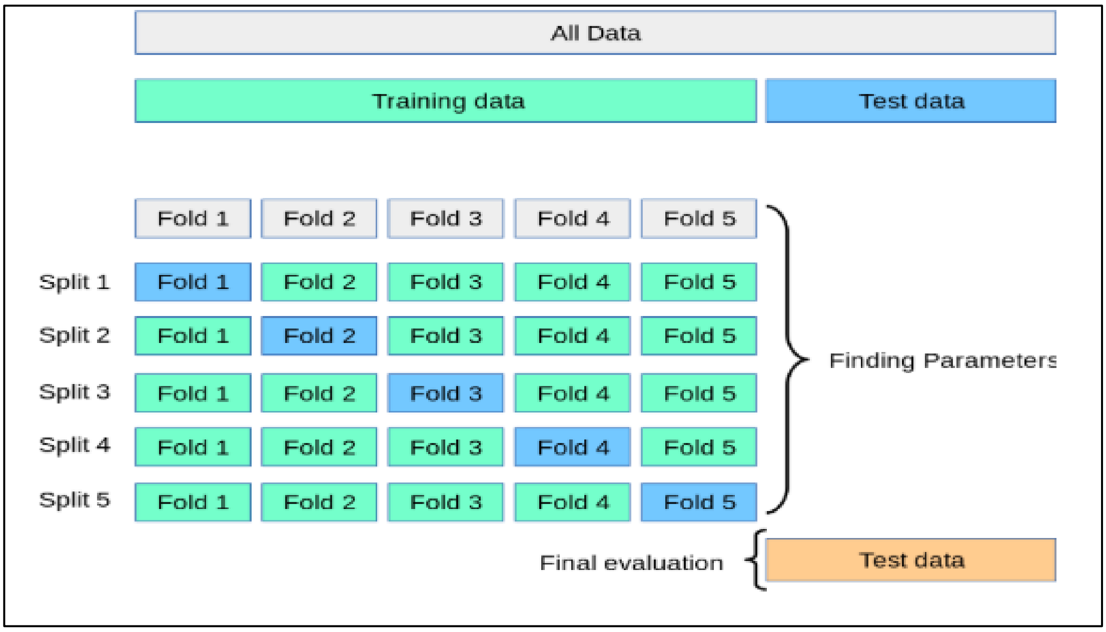

Figure 8: Holdout validation and K-fold cross-validation [32].

Sensitivity measures the proportion of actual positive cases that got predicted as positive (or True Positive (TP)) using Equation (7), while specificity measures the proportion of actual negative cases, which got predicted as the negative (or True Negative (TN)) using Equation (8). Accuracy, on the other side, is defined as the number of correct predictions over the total number of predictions [33], which can be found using Equation (9):

$$Sensitivity = \frac{TP}{TP + FN} \tag{7}$$

$$Specificity = \frac{TN}{TN + FP} \tag{8}$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{9}$$

1.7. Problem Statement

All industries in general and hospitals, in particular, should aim to use the appropriate maintenance strategy that ensures applying the right action at the right time to save time, efforts, and money. According to Mobley [2], maintenance is a huge part of any industry and it represents around 15% to 60% of the total cost. In the United States, industries are spending each year more than $200 billion on maintenance. Unfortunately, 33% of maintenance costs are due to improper and unnecessary maintenance actions.

Applying a PdM strategy can help in reducing unbeneficial maintenance actions and therefore reduce the wasted cost. This revolutionary approach can play a role key in improving the future of the healthcare industry; as compared to the traditional maintenance strategies implemented nowadays. Both RTF and PM strategies are showing an unsynchronized relationship with the fast-growing advanced technologies that demand continuous monitoring to prevent the error before it occurs.

Following a strategy that collects real-time data enabled by IoT will reduce time and help in failure diagnosis. This will increase the availability of equipment which will improve customer satisfaction and reduce risks.

This work proposes an IoT based maintenance approach that will take advantage of using the internet to help in monitoring and collecting data continuously. The work is carried out in collaboration with a local hospital- Sharjah, specifically in the laboratory department, where we had the chance to explore and check different machines and pick up the most suitable one for this study according to the proposed criteria. The proposed methodology will help in diagnosing the failures of machines which will have a positive impact on the hospital, patients, and industry.

1.8. Thesis Objectives

The objective of the research is to propose an IoT based approach to help medical equipment maintenance crew in diagnosis and failure prediction. Successful implementation of the proposed IoT approach will result in reducing both cost and repair time. Instead of purchasing all the spare parts for stock, the right planning will give industrial facilities enough time to order the spare parts or replacement at the right time.

When using the IoT in the maintenance process, monitoring the health status of the system will allow the prediction and prevention of failures. Specifically, the use of IoT with the PdM can provide a complete solution for industries that are always trying to find the best and suitable methods to increase the end user's satisfaction, reduce cost, time, efforts, and enhance the reliability of the system.

In the IoT framework, not only the sensors and devices that are connected, but also the users and technicians who are responsible for the maintenance process will have access to the information continuously and therefore reducing their efforts.

The IoT with the help of the wireless network sensors will play a big role in making better decisions for scheduling the maintenance actions.

1.9. Research Contribution

The contribution of this research is proposing a methodology that is based on the use of PdM strategy and IoT to be implemented in healthcare facilities to determine the equipment's failures before their occurrence. Data on the vibration parameter from the equipment will be collected and then analyzed using the most appropriate model which will allow technicians to indicate early faults and have enough time to prepare and schedule for the maintenance action. The use of IoT will facilitate the task by sending the collected data from the equipment through the internet, which provides the ability for continuous monitoring of the equipment’s condition. The impact of this approach will be reflected in cost, time, efforts, and equipment’s lifetime.

1.10. Thesis Organization

The rest of the thesis is organized as follows: Related works of this research are discussed in Chapter 2. The method to be followed is discussed in Chapter 3. Chapter 4 presents results and analysis. Finally, Chapter 5 concludes the proposal and outlines future work.

Chapter 2. Literature Review

Literature is rich with research carried out in the area of medical equipment maintenance. In this chapter, the surveyed literature will be divided into the following sections: PdM, maintenance in healthcare, IoT and maintenance, fault diagnosis and prognostics, failure mode and effect analysis, and fault detection tool selection methods.

2.1. Predictive Maintenance

According to Selcuk et al. [34], the concept of PdM was introduced since around 1940. However, at that time, experienced technicians used to depend on their senses of hearing, smelling, seeing and touching to figure out any sign that might be an indication of a problem. Nowadays, the concept of PdM has developed to replace the senses of humans used for failure detection, to the use of sensors. This strategy by many is considered to be the latest maintenance strategy.

Generally speaking, the PdM strategy is responsible for collecting data to determine the right time to take the right action, not only predict failures, but improve the quality of the operating equipment, enhance safety, and increase reliability and availability. The basic three steps toward building a PdM program involves data acquisition, data processing, and decision making. Implementing such a strategy will have positive impacts on the product lifetime and quality, lead to higher levels of safety and reduced times of breakdown and emergencies which can threaten people's lives [35].

Different PdM techniques can be applied to evaluate the condition of the equipment such as vibration, oil analysis, thermography, etc. Such techniques can be capable of detecting symptoms of defects and help in diagnosing these defects and determine their level of severity [35].

Vibration analysis is one common technique that is used for rotating machinery. It assists in determining the mechanical and functioning condition of the machine. A very important advantage of this technique is the ability to detect the defects before they become very serious to the level where the system breaks down. If these analyses are done in the right way, technicians will be able to evaluate the equipment state and prevent future failures. Generally, using this technique can give very early indications and in some cases even before months of the failure occurrence [36].

Real-time health monitoring of industrial components and systems that can detect, classify and predict impending faults is critical to reducing operating and maintenance costs. System condition is evaluated by processing the information gathered from controllers or sensors mounted at different points in the system, and maintenance is performed only when the failure/ malfunction prognosis indicates a potential failure instead of periodic maintenance inspections [37].

Garcia et al. [38] conducted a study on wind turbine gearbox involves using an intelligent system for PdM that is based on a software application that utilizes the collected data and information by sensors to detect any abnormality in the behavior of the system. Moreover, continuous real-time monitoring can help in estimating the health state of the gearbox and therefore scheduling the needed maintenance actions.

Susto [39] suggested that the rising need for reducing the number of downtimes and the number of costs associated with the traditional maintenance approaches are driving industries to adopt the PdM strategy. This study was performed on semiconductor manufacturing machines to test the effects of wear and tear associated with the usage and stress on the equipment part. A multiple classifier machine learning methodology was successfully implemented which enhanced the equipment performance and reduced the operating costs in comparison to PM and RTF approaches.

Similarly, Abbasi [40] stated that performing PM strategy in the oil and gas industry is highly costing due to either over-maintenance actions or the unexpected downtimes of the machine. Therefore, applying PdM which is based on real-time monitoring to estimate the health condition of the equipment can predict future failures and avoid the unnecessary maintenance actions which reduce the costs. In Abbasi’s research, a user-friendly Graphical User Interface (GUI) was developed which is based on the multiple linear regression PdM technique to enhance the accuracy of future predictions.

Maritime systems are operating in a very sensitive environment, where a breakdown can have very bad consequences that lie in the loss of revenues and high logistics charges due to remote locations. Tinga [41] has addressed this issue and mentioned that PM approach has been useful in reducing the number of failures but still considered an expensive method in addition to the constraint of system availability every time the maintenance action needs to be performed. Alternatively, the prediction of failures using PdM will result in reducing the times of maintenance actions which will increase the availability and reduce costs associated. This study suggests that both data-driven prognostics and physics-based prognostics models can be used for better results of failure prediction.

2.2. Maintenance in Healthcare

Healthcare technology management involves having a maintenance program that considers the characteristics and failures of medical equipment. According to the different characteristics of old equipment and new equipment, different maintenance strategies have to be used to increase the efficiency of the maintenance program.

Based on research work, Taghipour et al. [42] have proposed a multi-criteria-decision-making model that prioritizes medical devices based on their criticality. Medical devices will be scheduled for maintenance in the maintenance management program according to the criticality score that will be determined using the previous model. Devices with lower scores will have lower priority in the maintenance management program, while those with higher scores will be studied in detail to determine the reasons behind their high criticality and therefore use the appropriate maintenance strategy. Based on the different classifications of devices, different maintenance strategies will be used. In this work, 26 medical devices were used to set up the model.

According to Arunraj [43], the increase in the complexity and variety of medical equipment is a challenge that is affecting the maintenance management program, since different aspects need to be taken into considerations. These aspects include personnel and equipment safety, environmental compliance, and quality of services.

Sezdi [44] on the other hand, suggested using the corrective approach for the old equipment and the use of the PM approach for the recent ones. This suggestion is based on considering the characteristics of medical devices to increase the efficiency of this maintenance management program. For PM, devices were subjected to safety tests. However, for PdM manufacturers’ recommendations were followed.

Sipos et al. [45] have compared the scheduled maintenance (PM) and PdM. Scheduled maintenance is being performed in a wide range to ensure the appropriate functionality of the equipment and therefore avoid unexpected failures. Most of the times each component is being scheduled for maintenance separately based on its usage or after a certain period time. However, this strategy seems to be labor-intensive and ineffective in identifying problems that develop between the technician's visits. In contrast, PdM helps in predicting the time and the type of failure that might occur, by getting information regarding the condition of the medical equipment. This can be achieved by using sensors and mount them on the side of the equipment for the continuous monitoring of the equipment different parameters such as temperature and voltage. When the readings of the sensors exceed certain limits, a warning alert will be generated. Even though this approach can be effective, when it comes to in-service equipment it becomes impractical due to the infeasibility of adding sensors to the equipment and the need for many efforts and potentials. Instead, studying the logs of the equipment can give information about the condition, such as the error messages and internal states. These logs are generated by the software applications which operate the equipment. Analyzing the information can help in detecting potential problems in advance.

2.3. IoT and Maintenance

IoT is playing an important role nowadays in different industries, it is becoming a tool that facilitates maintenance actions. Bayoumi and McCaslin [46] used the PdM strategy as a tool that can be applied in different industries and users can be educated and trained to use it. The method starts with data collection using wireless sensors, then analyzing the data and modeling it using diagnostic and prognostic models to find out the Remaining Useful Lifetime (RUL). Finally, the information will be displayed for the technicians so that they can build up decisions related to the system status. To manage the data easily collected from the network sensors, cloud computing needs to be involved. Cloud computing will provide internet-hosted servers that will be able to store, manage, analyze the data and then share it across the whole network. This will give the user wide access to the database in which will help diagnose and generate reports.

They applied the method to general machinery. The test was done on gearbox by fitting temperature and vibration sensors into it. The data sensed was continuously compared with historical data stored already. After that, a thermal fault was introduced, and the temperature readings started to rise compared to normal readings. The fault model detected the fault and then alerted the user.

Dong et al. [47] proposed a PdM system based on the integration of IoT to change and develop the traditional PM strategy used for coal mining equipment. The main reason for applying this system to increase the safety of the coal mining process. The system was composed of an equipment state monitoring station, a coal mining monitoring center, and a remote predictive system. Equipment state monitoring station communicates with the coal mining monitoring center using a wireless network. Mining monitoring center receives the data of different parameters from the equipment monitoring station then data to be analyzed by the remote predictive system. After that, the information is stored in the database for evaluation, generating workloads, and creating reports. Engineers and technicians will be able to access the information in the predictive system and then they can check the state of the various devices and compare it with historical data and therefore predict faults. In this research, mining ventilator equipment was used as an example.

The global market of PdM is booming as the dependency on big data and IoT is rising [48]. One of the most valued applications of IoT is PdM. According to market research future report [49], it is expected that the global PdM market will grow at 6.3 billion dollars by 2022 and at 27% of Compound Annual Growth Rate (CAGR). With the introduction of IoT, PdM usage among manufacturing companies is expected to grow up to 83% in the coming two years [50]. Among its current deployment, the CXP Group report showed that 91% of PdM manufacturers reordered a reduction in repair time and unplanned downtime. Another report done by PWC reveals that PdM is expected to reduced cost by 12%, increase uptime by 9%, reduce safety, health, environment, and quality risks by 14% and extend the lifetime of an asset by 20% [49].

With the introduction of 5G, the global IoT market is growing rapidly as it assists businesses in optimizing the current operations and creates new models. In the following, some forecasts and market estimates of IoT are described. According to International Data Corporation (IDC), the IoT worldwide technology spending is expected to reach 1.2 trillion US dollars in 2022 and a CAGR of 13.6% over the forecasted period 2017-2022. The leading sectors for IoT spending growth are consumer, insurance and healthcare provider industries. Bain Company anticipates IoT combined market to grow about 520 Billion US dollars in 2021 which is double the spent in 2017 [51]. According to IoT analytics, the global IoT market is anticipated to grow at 39% CAGR over the forecasted period 2017- 2025 [51].

IoT in the healthcare industry is gaining an increasing momentum due to its unlimited applications resulting in enhancing the quality of the industry and the satisfaction levels of patients. Hospitals, for example, are putting great effort into applying IoT technology so doctors can monitor their patients; by using the wireless and sensing techniques, costs will be reduced, and work will be done efficiently. Another area of application is to enable technicians and engineers to monitor the medical devices continuously, helping in their management to maintain high-level performance anytime and anywhere [52].

Monitoring Electrocardiogram (ECG) signals using IoT is one application where sensors will collect the heart rhythm signals from patients then send them through the internet to the central station, so doctors and nurses can view the information and monitor the patients continuously. Several studies have discussed this approach [53], [54], [55], [56], [57].

Nurdin [52] model was made of ECG hardware, transmission module based on Zigbee and web server for data storage and web application. The ECG signal was recorded from the patients using an ECG machine with the help of the disposable electrodes that will convert the ionic current in the patient’s body into an electronic current, and then raw data was sent serially to the computer server using Zigbee. The data will be used for diagnosis and treatment, Figure 9 is displaying graphic samples of two patients. Doctors will be able to evaluate the measured signals and detect the abnormalities.

The testing results in Figure 10 are showing that the system can handle up to 20 users without errors. Meanwhile for 50 – 150 users some errors occurred due to insufficient bandwidth or high data traffic on the server. Nurdin [52] suggested increasing the capacity of the server to handle more users.

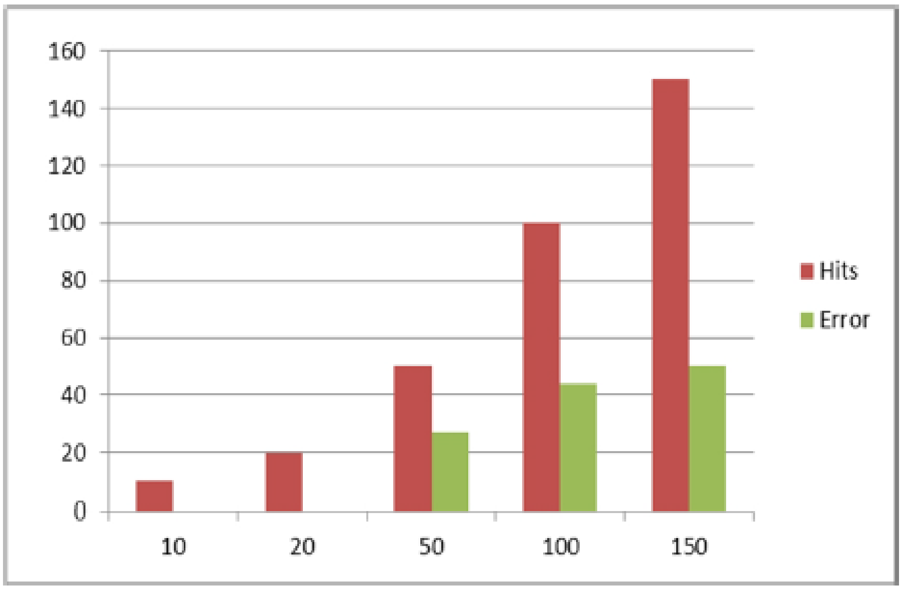

Figure 9: Testing results [33].

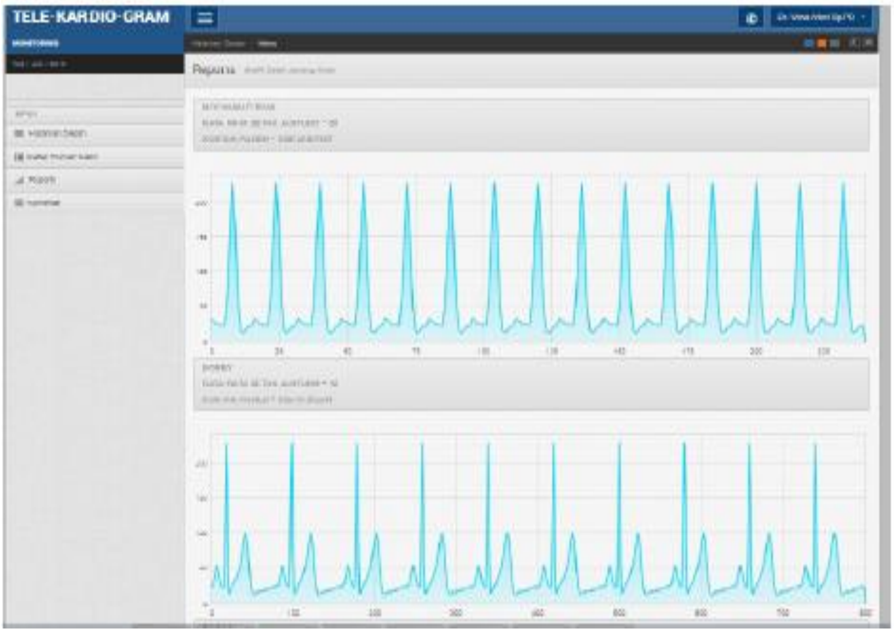

Figure 10: ECG graphic samples for two patients [33].

2.4. Fault Diagnosis and Prognostics

When it comes to fault diagnosis methodologies, three common approaches can model the degradation cycle of an asset and estimate its RUL. The approaches are data-driven, physics-based, and hybrid approaches as illustrated in Figure 11 [58], [59].

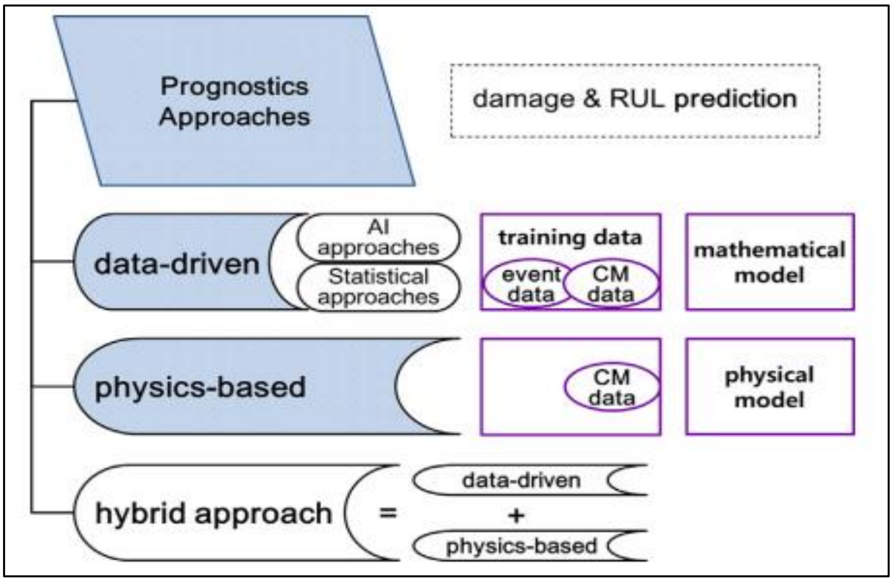

Figure 11: Prognostics approaches [60].

In a data-driven prognostics approach, a previously collected data is being used to understand and identify the properties of the progress of the damage and therefore predict the future state without the need to use a real physical system or model. Based on the obtained data under various conditions, suitable mathematical models can be employed [60]. Since the various approaches of the data-driven model depend on the trend of the data, they can be very useful in predicting the near-future trends.

As shown in Figure 11, the data-driven approaches can be divided into two main categories. The first category is the artificial intelligence (AI) approaches which include neural network (NN) [61], [62], 63] and fuzzy logic [64], [65]. While the second category is the statistical approaches that include Gaussian process (GP) regression [66], SVM [67], [68], least squares regression [69], the gamma process [70], the Wiener processes [71], and hidden Markov model [72].

Physics-based prognostics approach involves monitoring a certain physical model in normal and abnormal conditions using hardware systems and sensors to obtain the damage progress and estimate the RUL. The RUL is predicted by progressing the damage state until it reaches a threshold as indicated by the dashed curves in Figure 12 [60].

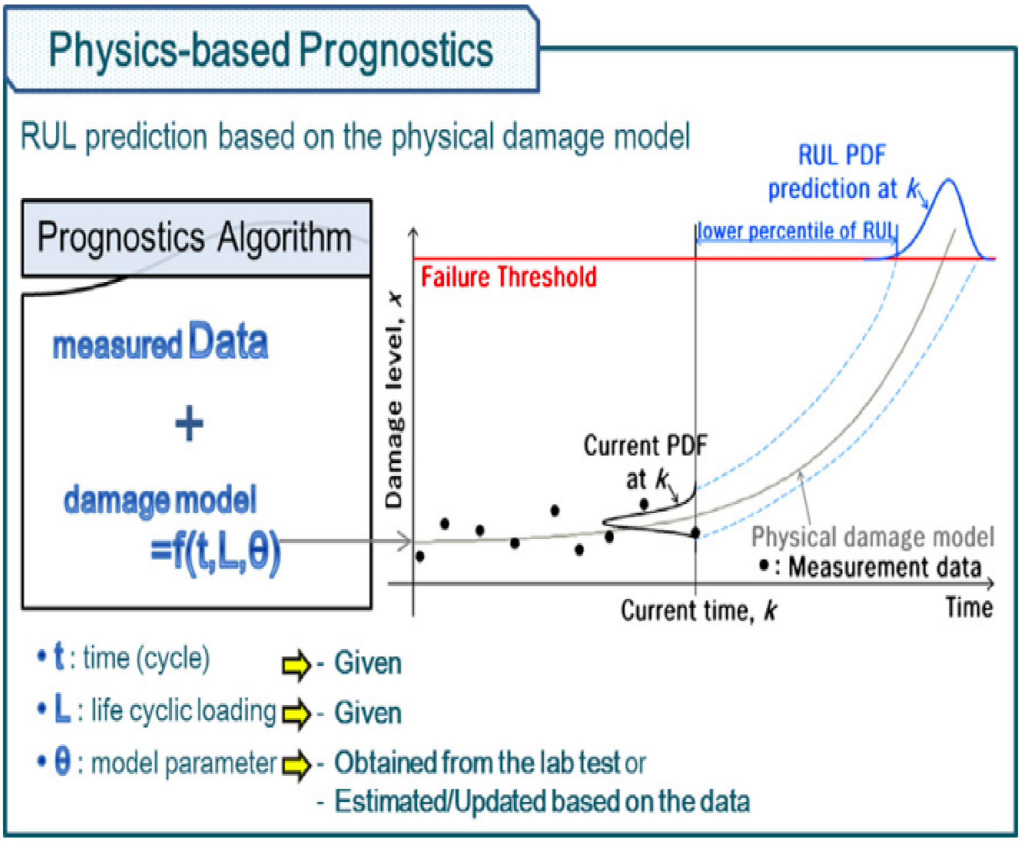

Figure 12: Physics-based prognostics [60].

The hybrid prognostics approach is composed of the two above mentioned approaches to enhance the prediction performance and allows better RUL prediction. It implies the advantages of the two previous approaches; precision and applicability [73].

2.5. Failure Mode and Effect Analysis (FMEA)

A step-by-step and systematic approach that was generated first in the 1940s by the U.S. military. It is considered to be a risk assessment tool in which can be used to identify all the possible failures for a certain design, product or equipment.

After that, multiple factors are taken into account to evaluate the equipment such as severity, occurrence and risk detectability as shown in Table 1. Such factors assist in classifying and prioritizing the different failure modes and help in coming up with actions that mitigate the risk [74].

Table 1: Failure mode and effect analysis (FMEA) [75].

Ranking	Severity	Occurrence	Detectability
1	No effect	Remote: Failure is unlikely <1 in 150,000	Design control will detect potential cause or the mechanism and subsequent failure mode
2	System operable with minimal interference	Low: Relatively few failures <1 in 150,000	Very high chance the design control will detect potential cause or the mechanism and subsequent failure mode
3	System operable with some degradation of performance	Low: Relatively few failures <1 in 15,000	High chance the design control will detect potential cause the mechanism and subsequent failure mode
4	System operable with significant degradation of performance	Moderate: Occasional failures <1 in 2000	Low chance the design control will detect potential cause the mechanism and subsequent failure mode
5	System inoperable with no damage	Moderate: Occasional failures <1 in 400	Moderate chance the design control will detect potential cause the mechanism and subsequent failure mode
6	System inoperable with minor damage	Moderate: Occasional failures <1 in 80	Low chance the design control will detect potential cause the mechanism and subsequent failure mode
7	System inoperable with equipment damage	High: Repeated failures <1 in 20	Very low chance the design control will detect potential cause the mechanism and subsequent failure mode
8	System inoperable with destructive failure without compromising safety	High: Repeated failures <1 in 8	Remote chance the design control will detect potential cause the mechanism and subsequent failure mode
9	Very high severity ranking when a potential failure mode affects safe system operation with warning	Very high: Failure is almost inevitable <1 in 3	Very remote chance the design control will detect potential cause the mechanism and subsequent failure mode
10	Very high severity ranking when a potential failure mode affects operation without warning	Very high: Failure is almost inevitable <1 in 2	Design control cannot detect potential cause the mechanism and subsequent failure mode

2.6. Fault Detection Tool Selection Method

Numerous algorithms are being used to process signals, classify, and validate them as described in Table 2.

Table 2: Characteristics of commonly used algorithms [87].

Algorithm	What is it used for?	Advantages	Disadvantages
Fourier Transform [88], [89]	• To represent a waveform in the frequency domain. • It decomposes or separates the waveform into a sum of sinusoids of different frequencies.	• Appropriate for stationary signals. • Presents signal with good spectrum resolution.	• Lack of temporal information. • Not appropriate for non-stationary signals.
Principal Component Analysis (PCA) [90], [91], [92], [93]	• To reduce the dimensionality by transforming the original features into a new set of uncorrelated features.	• Reduces multi-dimensional data sets to lower dimensional data sets.	• Its performance varies for different applications. • Linear transformation.
Support Vector Machine (SVM) [94], [95], [96], [97]	• To project feature space into a higher dimensional space by a kernel function. • To find an optimized separation hyperplane in the projected space to maximize the decision boundary.	• Achieves better decision accuracy in special cases because of the maximized decision boundary. • Efficient for a large dataset and real-time analysis.	• No standard method to choose the kernel function which is the key process for SVM.
Decision Trees [98], [99], [100], [101]	• Classify data item by starting at the root node of the tree and following the assertions down until reaching a terminal node (leaf of tree). • A special form of a rule set, characterized by the hierarchical organization of rules.	• Good visualization, easy interpretation and quick analysis ability for decision making.	• Need high-level experience and knowledge to formulate the tree structure.

The most common algorithms for signal processing and classifications were summarized in Table 2 along with the various applications, in addition to their associated advantages and disadvantages when it comes to the field of selecting the best method for fault detection.

Kulkarni et al. [76] discussed a machine learning-based method to overcome problems related to refrigerates and cold-storage systems. In such environments, temperature and defrost readings are needed. To detect any future presence or absence of any problem in a certain refrigeration case in a certain time, the extracted features to learn a random forest-based binary classifier are used. The data used in this approach was for 2265 refrigeration cases across seventeen supermarkets with a precision of up to 89%.

A study conducted by Konar [77], on bearing fault detection scheme of three-phase induction motor where SVM was used to analyze the frame vibrations during start-up. Results showed that SVM classifier gave excellent result since it is very simple and easy to implement compared to Artificial Neural Networks (ANN) based approach which requires an exhaustive task of trial and error process for determining the most optimum model.

In [78], Chen et al. developed an SVM model to improve the efficiency of equipment in a thermal power plant. The proposed model integrates a dimension reduction scheme to analyze the failures of turbines in thermal power facilities. Also, a real case was provided from a thermal power plant to evaluate the effectiveness of the proposed SVM based model. Experimental results showed that SVM outperforms Linear Discriminant Analysis (LDA) and Back-propagation Neural Networks (BPNN) in classification performance.

Another study done by Hu [79] presents a novel method for fault diagnosis based on an Improved Wavelet Package Transform (IWPT), a distance evaluation technique and the SVM. The optimal features are input into the SVM to identify the different abnormal cases. The proposed method is applied to the fault diagnosis of rolling element bearings, and testing results showed that the SVM can reliably separate different fault conditions and identify the severity of incipient faults, which has a better classification performance compared to the single SVM.

A published paper by Ye Zhao et al. [80] showed that because of the non-linear output characteristics of photovoltaic arrays, a variety of faults may be difficult to detect by conventional protection devices. To detect and classify these unnoticed faults, a fault detection and classification method has been proposed based on decision trees. In experimental results, the trained decision tree models have shown a high accuracy of fault detection and fault classification on the test set.

Based on Sun [81], data mining technology was introduced to the rotating machinery fault diagnosis field and the decision tree was proposed to make fault diagnosis of rotor faults. PCA was used to reduce features after data collection, preprocessing and feature extraction. Then, the decision tree was trained by using the samples to generate a decision tree model with diagnosis knowledge. The result showed that the decision tree and PCA-based diagnosis method has higher accuracy and needs less training time than BPNN.

According to Huang et al. [82], the main criterion to evaluate and compare the classification's algorithms in terms of their predictive performance is the prediction accuracy percentage.

One study conducted by [83] in image classification area has used two classifiers, SVM and decision trees, to investigate a new approach in this field. SVM types that were used are linear, polynomial, and Gaussian. The overall accuracy of the SVM showed higher percentages (73%) in comparison to the decision trees algorithm (69%), which indicates a better image classification when using the SVM algorithm.

In [84], Mayasari compared the performance of SVM and decision tree methods in predicting graduation time. Results revealed that the decision tree algorithm outperforms SVM in terms of computing speed. However, both methods showed a balanced level of accuracy.

Authors in [85], conducted a comparative study of machine learning algorithms, SVM, K-Nearest Neighbors (KNN), and decision tree to predict student's performance. Initially, the data was collected, and then the three models were built, to perform the comparison and evaluation analysis. Results showed that SVM has the highest prediction accuracy of 95%, while the decision tree has 93% and KNN has a 92% prediction accuracy value.

Huang et al. [86], assessed the use of SVM for high dimensional data sets for land cover classification from satellite images. SVM was analyzed and compared with other classifications which are the Maximum Likelihood Classification (MLC), NN, and decision tree classifiers. The comparison was made based on accuracy, stability, and training speed criteria. Comparing the four algorithms, results showed that SVM is more accurate and stable than the other classifiers. Out of the 24 training cases, 22 cases revealed that SVM has higher accuracy than the decision tree. In terms of investigating the impact of selecting training samples, all four classifiers were affected.

The literature and previous studies reveal that the implementation of an IoT-based predictive approach is yet to be explored especially in the healthcare industry. This was the main motivation for our present study. In this study, we propose an IoT-based PdM strategy using a machine learning approach. Chapter 3 well details about the methods used for implementing this study.

Chapter 3. Methodology

Figure 13 outlines the proposed approach for managing and optimizing medical equipment maintenance using IoT based structure. The steps that will be followed to deal with the problem are discussed as follows:

Step 1:	• Review maintenance logs and collect failure related information.
Step 2:	• Equipment criticality assessment criteria.
Step 3:	• Develop FMEA for the critical equipment.
Step 4:	• Determine the most appropriate maintenance strategy.
Step 5:	• Needed feature for fault detection.
Step 6:	• Collect sensor data.
Step 7:	• Feature extraction.
Step 8:	• Feature selection.
Step 9:	• Determine best classification method.
Step 10:	• Evaluate economic feasibility of IoT solution.

Figure 13: Methodology steps

3.1. Review Maintenance Logs and Collect Failure-related Information

The first step towards building the methodology is reviewing incidents and maintenance orders log for medical equipment. This step will give a better idea regarding the issues that arise in the equipment and will allow us to track the maintenance history of each asset. Thus, we can collect fault data, the number of failures, time to repair, and cost to repair related to some equipment.

3.2. Equipment Criticality Assessment Criteria

The purpose of this step is to figure out the equipment with the highest negative potential consequences on business performance. Determining the criticality of equipment can be achieved by finding out failure occurrence, usage, and equipment importance. Based on these criteria the medical equipment will be selected for the study.

3.3. Failure Modes

FMEA is the tool that will be developed for the critical equipment to discover and identify the associated failure modes and their effect on the functionality of the equipment, and thus the corresponding needed actions to fix the problem. This will help in ranking the issues in terms of their importance so that corrective actions can be performed. Choosing the most critical failure mode will be done through finding the Risk Priority Number (RPN) which is the measure for assessing the risks associated. RPN can be calculated by multiplying the severity, occurrence, and detectability, and the failure with the highest RPN will be the most critical one.

3.4. Determine the Most Appropriate Maintenance Strategy

Based on the failure modes and the nature of the equipment that needs to be taken into consideration, we will determine the most appropriate maintenance strategy to follow, whether it is PM, PdM, or RTF, that will have the highest impact in terms of costs, efforts, and personnel safety.

3.5. Needed Feature for Fault Detection

For predictive failure modes, determine based on physics, the needed feature for fault detection and the method to collect data for this feature. Examples of features are voltage, current, or vibration.

3.6. Data Collection

The following step towards building a PdM approach is data collection through using sensors mounted on the device. A Wireless Sensor Network (WSN) consists of sensor nodes, each of which is equipped with a radio transceiver, a small microprocessor, and several sensors can be used. These nodes can autonomously form a network through which sensor readings can be propagated. Since the sensor nodes have some intelligence, data can be processed as it flows through the network.

3.7. Signal Processing and Features Extraction

Signal pre-processing is aiming to enhance the characteristics of the signals, which might lead to easier extraction of the useful information related to the condition that is being monitored and even more efficient. The tools that can be used in this step may involve signal filtering, amplification, correlation, and compression to reduce artifacts and noise levels for a better quality of the signals. Extracting features from the pre-processed signals is then performed which can be an initial indicator for a fault or failure [102].

3.8. Feature Selection

After extracting the features from the signals, features selection which involves selecting the most significant and contributing features can be performed using PCA. In some cases, where the selection of significant features is not applicable, PCA can be used to describe around 90% of the extracted features using principal components that were described previously in Chapter 1.

Correlation is another tool that can be used for features selection. In such a case where more than one sensor is used, a correlation between the sensors can be applied to determine their relationship, if they are correlated, then we can select one of them and drop the other.

3.9. Classification

Different models can be used to analyze, and classify the data, therefore predict the future status of the component or system. For example, the logistic regression model is used to determine whether an observation is falling in the safe range or critical range. Historical data with this model will be needed to create the initial model which will be able to detect the failure. This will be done by comparing the real-time data with the historical data to detect if there is any abnormal change that might lead to failure. Different statistical models will be considered for this work such as SVM and decision trees. Based on the accuracy percentages, the best classifier will be determined.

3.10. Economic Feasibility of IoT Solution

By connecting the sensor network to existing network infrastructure such as the global Internet, a local area network, or a private intranet, gaining remote access to the sensor network is straightforward. Dealing with signals coming from sensors can be done and data analysis is then performed that allows the technicians and engineers to monitor the condition of the system continuously.

After proposing our system, a cost/ benefit analysis will be performed to estimate the costs and revenues of implementing the PdM system by taking into considerations all the requirements that are needed for applying the system. The proposed approach will be demonstrated using medical equipment of a local hospital.

Chapter 4. Results and Analysis

In this chapter, the experimental results and analysis of implementing the predictive approach are discussed, in addition to the costs and benefits of the proposed approach.

4.1. Review Maintenance Logs and Collect Failure-related Information

In collaboration with a local hospital- Sharjah, they were able to provide us with the most failing machines in the hospital in addition to the total breakdowns of these machines for the years 2015, 2016, and 2017 as shown in Table 3. Besides, the maintenance log of the machine is described in Table 4, Table 5 and Table 6. The minimum time taken to fix a failure is around one day, and the opportunity cost for one failure is around AED 10,000 per day.

Table 3: Most failing medical machines in the local hospital.

#	Equipment Name	Department	Total Breakdown 2015	Total Breakdown 2016	Total Breakdown 2017
1	Vitros Immunoassay Analyzer	Laboratory	17	14	14
2	Integra 400 Plus Biochemistry Analyzer	Laboratory	16	14	13
3	Modular Auto Analyzer	Laboratory	15	15	9
4	Sysmex Hematology Analyzer	Laboratory	7	7	6
5	Elite Pro Coagulation Analyzer	Laboratory	10	8	1

4.2. Equipment Criticality Assessment Criteria

Among the previous machines which are working in the laboratory department 24/7, we have chosen Vitros Immunoassay Analyzer as shown in Figure 14 for our work since it is the most failing equipment in the laboratory department. The Vitros analyzer is immunodiagnostic equipment which is responsible for performing several medical blood tests such as HIV, BHCG, and Hepatitis.

Figure 14: Vitros Immunoassay Analyzer.

4.3. Failures Criticality Analysis

After monitoring the equipment for three months we were able to identify the failure modes associated which are explained in Table 7.

We found that most failures are due to the mechanical movements of the parts. The most failing and critical part selection was based on the highest RPN score.

The most failing part was called the sample-metering arm as shown in Figure 15 which is responsible for drawing a certain amount of the sample from the sample tube through a cup, then mixing it with a specific reagent inside the incubator based on the requested test.

Table 4: Maintenance log.

Description	**Number of occurrences**	**Probability %**	**Fault mode**	**Probability % based on fault mode**	**Action taken**
Luminometer voltage/ temperature/ data is out of range	5	12.20	Electrical	46.34	Clean the sensors, check the power supply, recalibration
Reagent washing probe verification is outside acceptable limits	1	2.44	Electrical		Replace the pump if it is not functioning properly
The washing well temperature is out of range	1	2.44	Electrical		Monitor the environmental temperature and replace fluid heater if necessary
Sample- metering arm is not reaching home location, motor flag failure	10	24.39	Electrical/ Wear and Tear		Make sure door lock switch is locked, check the sample- metering probe if blocked using a syringe, if it is not working then replace the probe, re-adjust the belt

Table 5: Continue- Maintenance log.

Description	**Number of occurrences**	**Probability %**	**Fault mode**	**Probability % based on fault mode**	**Action taken**
Reagent metering performance is outside acceptable limits	2	4.88	Electrical/ Wear and Tear		Check reagent metering liquid level sensor and replace it if it is not functioning, check the reagent metering probe if blocked using a syringe, if it is not working then replace the probe
The inner ring is not reaching home/ washing well	4	9.76	Mechanical		Check the solid waste container if full then it needs to be emptied, reagent cups are stuck inside and need to be removed
Reagents loading is not working	2	4.88	Mechanical	46.34	Take out all reagents then reload them
Luminometer shuttle is not closing, the inner ring is not reaching the washing well	2	4.88	Mechanical		Check the position of the shuttle using a special tool

Table 6: Continue- Maintenance log.

Description	Number of occurrences	Probability %	Fault mode	Probability % based on fault mode	Action taken
Incubator shuttle is not reaching home location, water is leaking from bottom	1	2.44	Mechanical		Clean the sensors and check the position of the incubator shuttle using a special tool
Reagent shuttle is not moving	1	2.44	Mechanical		Replace the packed shuttle if broken or bent
Unable to move the reagent metering pump	2	4.88	Mechanical		Check the pump and replace it if it is not working
Unable to meter the sample fluid	7	17.07	Mechanical / Wear and Tear		Check the sample- metering probe if blocked using syringe, if it is not working then replace the probe
Calibration error	1	2.44	Software		Recalibration
The machine is not taking bidirectional commands	1	2.44	Software	7.32	Check the lab computer configuration, and check the communication cable
The incubator is filled with dust	1	2.44	Wear & Tear		Clean filter
The total number of faults:	41				

Table 7: FMEA.

#	Function	Failure Mode	Severity	Occurrence	Detectability	RPN
1	Sample-metering arm	Sample- metering arm is not reaching home location, motor flag failure	4	5	3	60
		Unable to meter the sample fluid	5	4	3	60
2	Luminometer	Luminometer voltage/ temperature/ data is out of range	3	3	2	18
		Luminometer shuttle is not closing, the inner ring did not reach the well	3	2	2	12
3	Incubator	Incubator shuttle is not reaching home location, water leaking from bottom	3	3	3	27
		Incubator filled with dust	1	1	2	2
4	Reagent	Reagent washing probe verification is outside acceptable limits	3	3	2	18
		Reagent metering performance is outside acceptable limits	3	2	2	12
		Reagents loading is not working	1	3	1	3
		Reagent shuttle is not moving	2	2	1	4
		Unable to move the reagent metering pump	2	2	3	12
5	Well	The washing well temperature is out of range	3	2	2	12
		The inner ring is not reaching home/ washing well	2	3	1	6

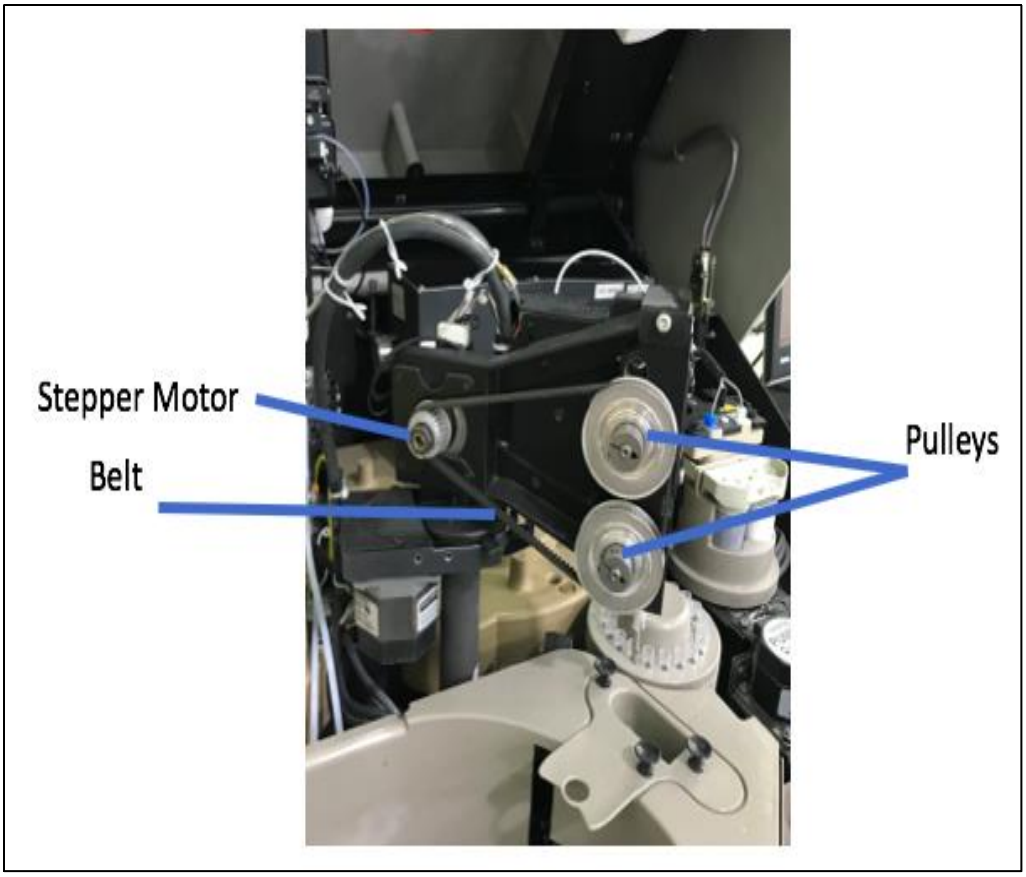

Figure 15: Sample- metering arm.

Four failure modes associated with the sample- metering arm which are: tube blockage, presence of air pressure in the tube, blockage in the sample-metering arm pump, and finally, wear and tear of the belt. We have started with the wear and tear of the belt which causes the belt to become loose due to the continuous use and movement of the sample-metering arm.

4.4. Determine the Most Appropriate Maintenance Strategy

To diagnose the failure related to the belt, we had to apply the predictive approach through collecting data from sensors being mounted on this part, but due to the hospital's regulations and restrictions we were not allowed to do any modification on any machine, so we had to simulate this part in our university lab using a 3D printer that had a similar part to the one shown in Figure 15.

4.5. Needed Feature for Fault Detection

Referring back to Figure 4 where we have the P-F curve, it shows that vibration signals are among the first ones to indicate the deterioration of the equipment. Besides, after studying the functionality of the machine we found that vibration signals are needed to be collected based on the nature of our part of interest.

4.6. Vibration Data Collection

Accordingly, two accelerometer sensors as shown in Figure 16 were mounted on the 3D printer to collect vibration signals for 30 repetitive cycles; which are considered to be healthy profiles of the extruder part that is attached to a belt.

After the collection of the 30 healthy profiles, we had to tighten the belt as shown in Figure 17 and recollect the vibration signals for 20 cycles that are considered now to be the faulty profiles. As a result, we had 50 profiles in total for each sensor where 30 profiles are healthy, and 20 profiles are faulty. Figure 18 and Figure 19 illustrate the vibration signals in the time domain for 8 seconds for the first and the second sensor respectively of both healthy, faulty, and both combined.

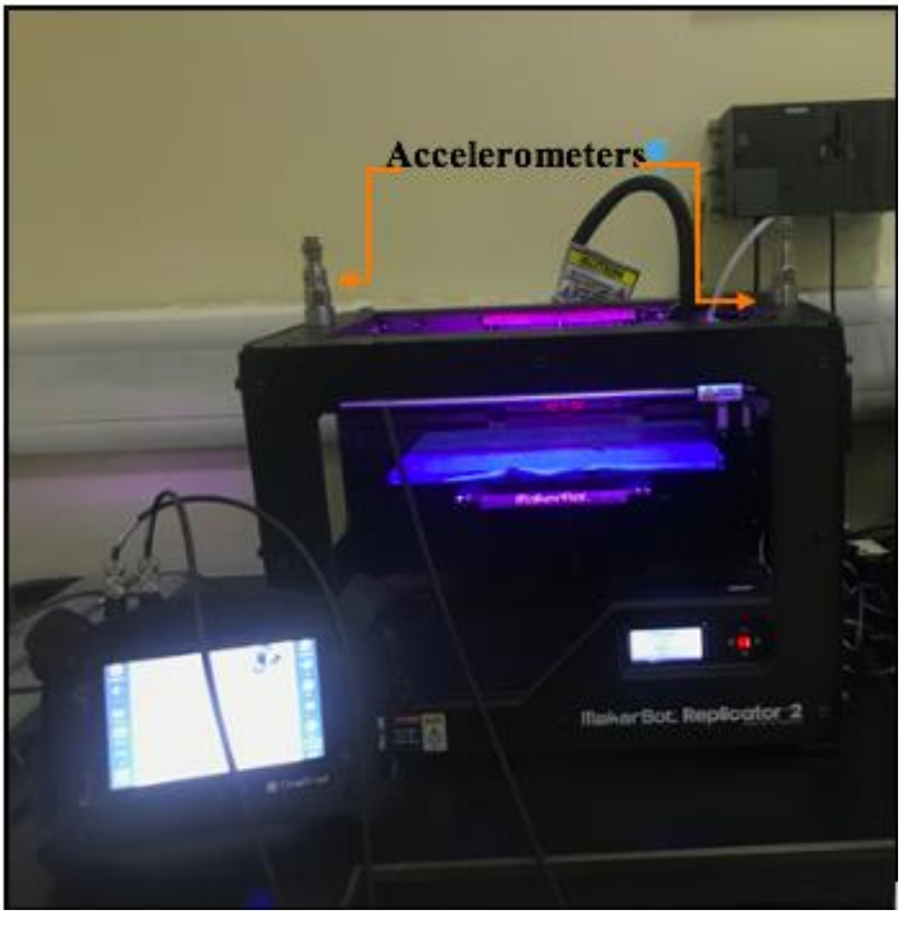

Figure 16: 3D printer used for simulation.

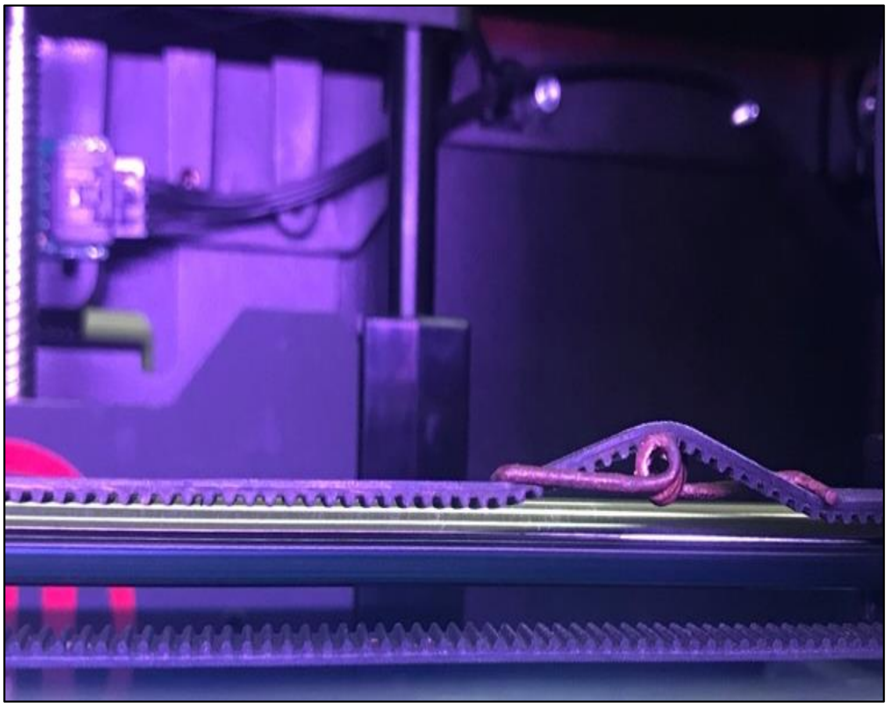

Figure 17: Extruder belt after being tightened.

4.7. Signal Processing and Features Extraction

Following the collection of the data, signals processing step is then performed in order to extract the useful information. Vibration signals were collected in the time domain, so we had to transform them into the frequency domain using the Fast-Fourier Transform (FFT) algorithm. This step provides a better extraction of the features since it is easier to interpret signals in the frequency domain. Using FFT enhances the Signal-to-Noise (SNR) ratio which measures the strength of the desired signal in comparison to the background noise. A high SNR means more reduction in the noise of the collected signals. Moreover, since the properties of the process that generates the signals do not change in time, then the process is stationary which makes the FFT a powerful and useful tool to be used in our case.

MATLAB software was used to process the signals and display them. Figure 20 and Figure 21 are illustrating the vibration signals in the frequency domain of an interval of 500 Hz for the first and the second sensor respectively of both healthy, faulty, and both combined.

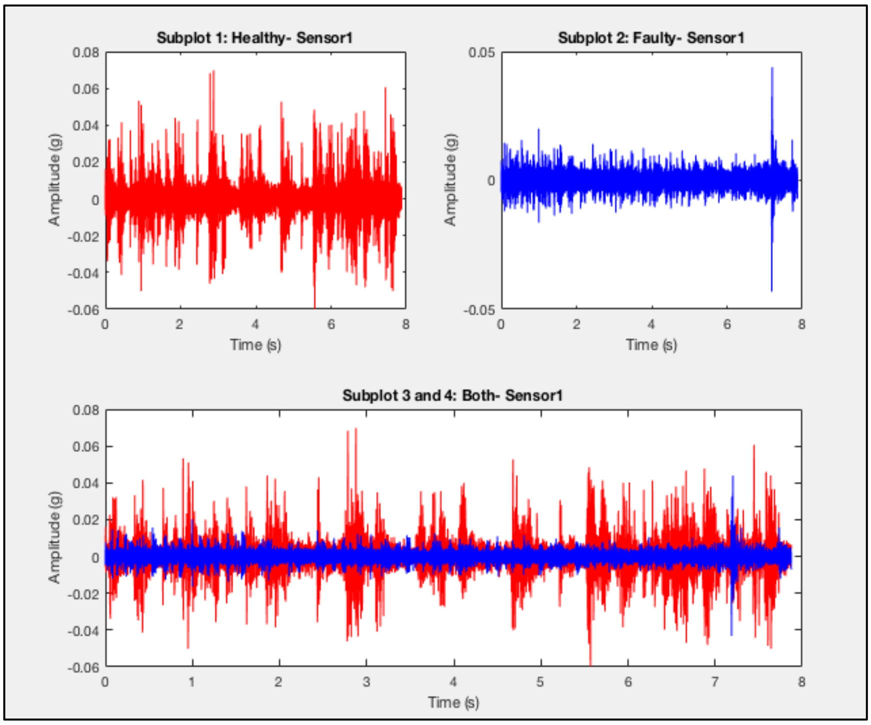

Figure 18: Sensor 1- Vibration signals in the time domain for healthy, faulty, and both combined.

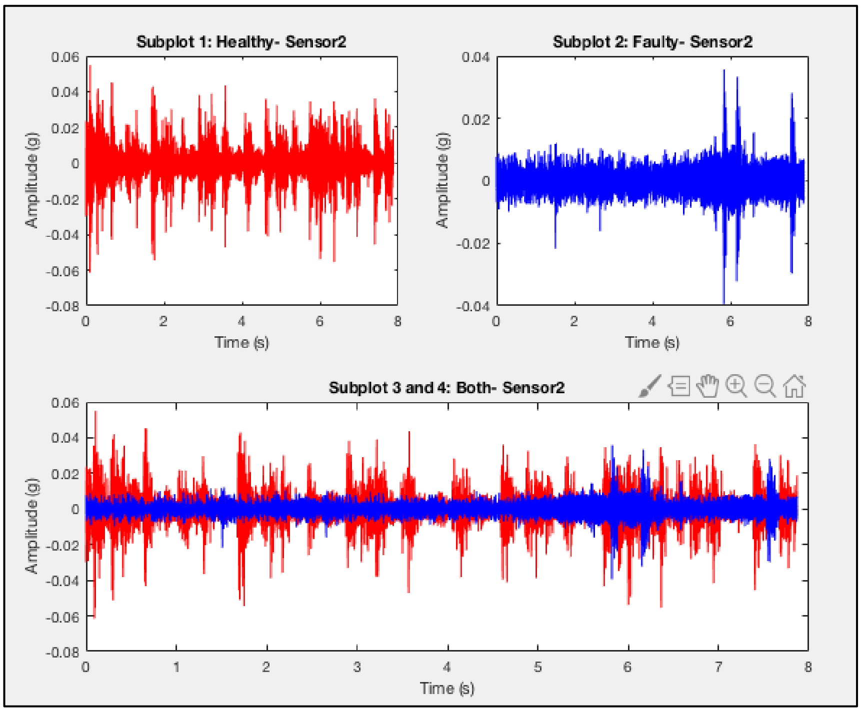

Figure 19: Sensor 2- Vibration signals in the time domain for healthy, faulty, and both combined.

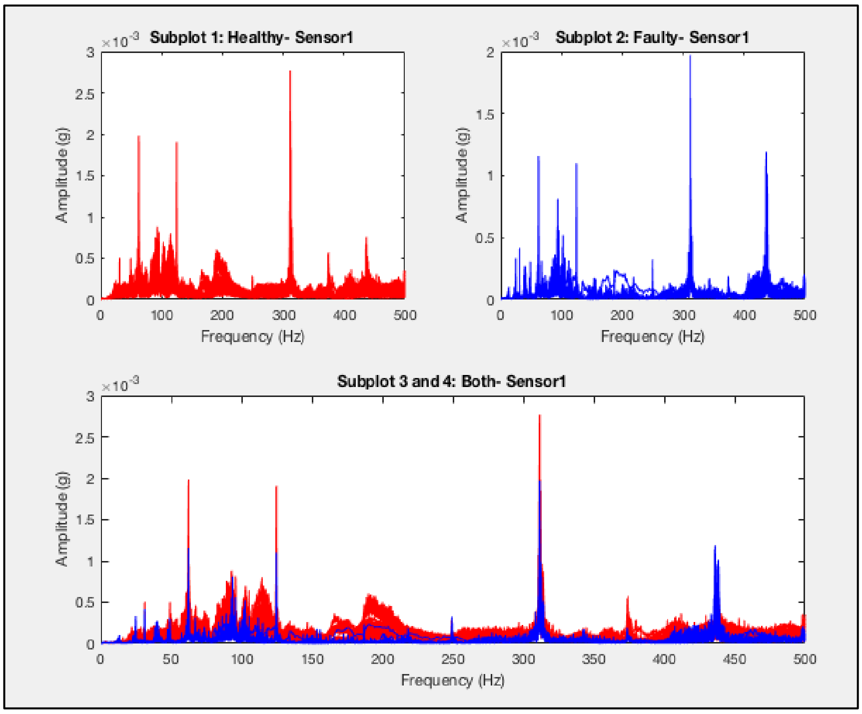

Figure 20: Sensor 1- Vibration signals in the frequency domain for healthy, faulty, and both combined.

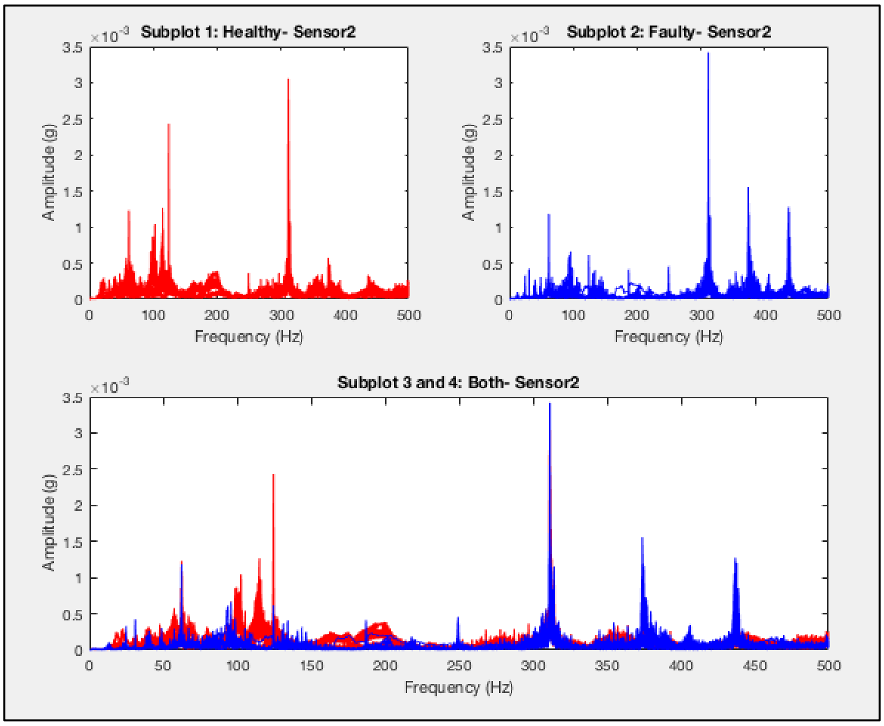

Figure 21: Sensor 2- Vibration signals in the frequency domain for healthy, faulty, and both combined.

Following the FFT, features extraction step was performed using 17 different features that were extracted from each frequency domain profile of the healthy and faulty measurements of the two sensors. Table 8 and Table 9 below summarize the extracted features and their formulas respectively where x_i represents the signal. According to previous studies, some features such as Root-Mean-Square (RMS), standard deviation, and variance were used most of the time to differentiate between vibration signals in addition to more advanced features such as skewness and kurtosis that can be used with stationary signals [103].

Table 8: Features extracted from the vibration signals in the frequency domain.

#	Feature Name	Formula	References
1	RMS	$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}$	[103], [104], [105]
2	Mean	$Mean\ (\mu) = \frac{\sum_{i=1}^{N} x_i}{N}$	[104]
3	Skewness	$Sk = \frac{\sum_{i=1}^{N}(x_i - \mu)^3}{(N-1)\sigma^3}$	[103], [104], [105]
4	Kurtosis	$Ku = \frac{\sum_{i=1}^{N}(x_i - \mu)^4}{(N-1)\sigma^4}$	[103], [104], [105]
5	Peak to peak	$P2P = 2\sqrt{2}\ RMS$	[104]
6	Standard deviation	$SD(\sigma) = \sqrt{\sigma^2}$	[104]
7	Crest factor	$CF = \frac{max\lvert x_i\rvert}{RMS}$	[103], [104]
8	Shape factor	$SF = \frac{RMS}{\lvert\mu\rvert}$	[103], [104]
9	Impulse factor	$IF = \frac{max(x_i)}{\lvert\mu\rvert}$	[104]
10	Margin factor	$MF = \frac{max(x_i)}{\left(\frac{1}{N}\sum_{i=1}^{N}\sqrt{\lvert x_i\rvert}\right)^2}$	[104]

Table 9: Continue- Features extracted from the vibration signals in the frequency domain.

#	Feature Name	Formula	References
11	Median	$MD = median\ value$	[106]
12	Maximum	$Max = max(x_i)$	[107]
13	Minimum	$Min = min(x_i)$	[107]
14	Mode	$Most\ frequent\ point$	[108]
15	Variance	$Var(\sigma^2) = \frac{\sum_{i=1}^{N}(x_i - \mu)^2}{(N-1)\sigma^2}$	[103], [104], [105]
16	Range	$R = max(x_i) - min(x_i)$	[107]
17	Energy	$E = \sum_{i=1}^{N} \lvert x_i \rvert^2$	[109]

4.8. Features Selection

After extracting the 17 features from the 50 profiles, PCA and correlation techniques can be used to check the possibility of reducing the number of features or reducing the number of the sensors that are used without losing information.

4.8.1. PCA. We applied the PCA to transform the set of correlated features that we extracted previously, into a set of linearly uncorrelated variables which are the principal components. Figure 22 and Figure 23 correspond respectively to the scree plots for the PCA analysis of sensor 1 and sensor 2.

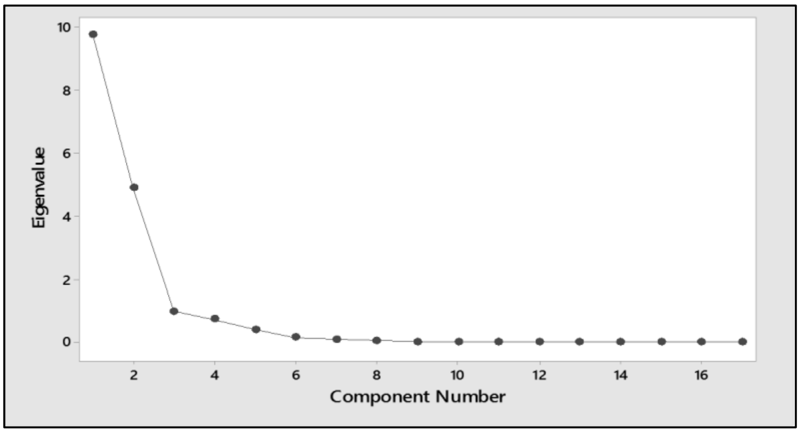

Figure 22: Scree plot for extracted features of sensor 1.

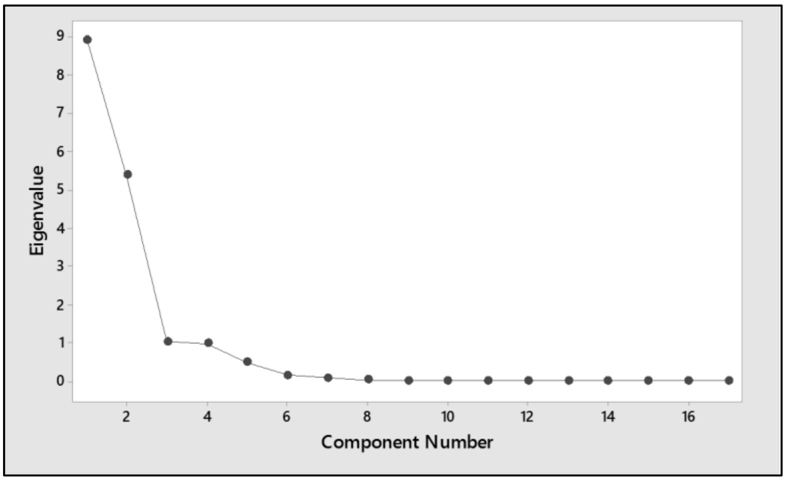

Figure 23: Scree plot for extracted features of sensor 2.

In the scree plot of sensor 1, the first 3 principal components account for approximately 92% of the total variance, while in the scree plot of sensor 2, the first 3 principal components account for approximately 90% of the total variance. An example of the variables that correlate the most with the first Principal Component (PC1) of sensor 1 is Mean (0.316), RMS (0.308), Median (0.307), and Energy (0.3607).

In our case, the performed PCA did not result in reducing the number of features, since all the principal components till number 16 were combinations of all the features, which means that we will be using them all in the classifications.

4.8.2. Correlation. It is a statistical procedure that measure whether pairs of variables are strongly related or not. After obtaining the values of the extracted features, we applied a correlation to these values that correspond to sensor 1 and sensor 2 to see the relationship between the two sensors.

Table 10 displays Pearson's correlation coefficients for the 30 healthy profile which measures the strength of the linear relationship between the two sensors, while Table 11 displays Pearson's correlation coefficients for the 20 faulty profile.

The correlation coefficients have shown a positive correlation between the two sensors, which in turn proves that one sensor is enough for collecting the data instead of using two sensors. This will have a positive impact on reducing the total cost that is associated with implementing the IoT-based PdM approach.

Table 10: Pearson's correlation coefficients for healthy profiles.

Healthy profile number	**Pearson's correlation coefficient**
Profile 1	0.576
Profile 2	0.628
Profile 3	0.509
Profile 4	0.673
Profile 5	0.667
Profile 6	0.692
Profile 7	0.744
Profile 8	0.662
Profile 9	0.705
Profile 10	0.719
Profile 11	0.609
Profile 12	0.686
Profile 13	0.605
Profile 14	0.759
Profile 15	0.630
Profile 16	0.551
Profile 17	0.416
Profile 18	0.537
Profile 19	0.533
Profile 20	0.470
Profile 21	0.622
Profile 22	0.449
Profile 23	0.531
Profile 24	0.441
Profile 25	0.658
Profile 26	0.280
Profile 27	0.653
Profile 28	0.488
Profile 29	0.533
Profile 30	0.431

Table 11: Pearson's correlation coefficients for faulty profiles.

Faulty profile number	Pearson's correlation coefficient
Profile 1	0.512
Profile 2	0.478
Profile 3	0.486
Profile 4	0.691
Profile 5	0.473
Profile 6	0.629
Profile 7	0.705
Profile 8	0.708
Profile 9	0.665
Profile 10	0.785
Profile 11	0.736
Profile 12	0.738
Profile 13	0.758
Profile 14	0.688
Profile 15	0.661
Profile 16	0.645
Profile 17	0.642
Profile 18	0.685
Profile 19	0.596
Profile 20	0.716

4.9. Validation and Modelling

Before training the classifiers, we need to test the different validation methods. For our case, we tested the holdout validation and the k-fold cross-validation.

Table 12 summarizes the used classifiers and their accuracy percentages for the first and second sensors respectively using holdout validation of 20% of the data being held for validation, and the k-fold cross-validation of 5 folds. The accuracy percentage of classifiers using holdout validation is the average of the accuracy percentage for each iteration.

Table 12: Accuracy percentages of the classifiers

Classifier	**Holdout**		**K-fold**	
	Sensor 1	**Sensor 2**	**Sensor 1**	**Sensor 2**
Fine Tree	90%	70%	94%	80%
Medium Tree	90%	70%	94%	80%
Linear SVM	100%	90%	96%	82%
Quadratic SVM	90%	90%	94%	84%
Cubic SVM	100%	80%	92%	78%
Fine Gaussian SVM	90%	90%	94%	84%

By observing the the results that were obtained for sensor 1 and sensor 2, we can see that for sensor 1, linear SVM in both holdout and cross-validation has obtained higher percentages of accuracy. Figure 24 shows the confusion matrix of the linear SVM using holdout validation, while Figure 25 shows the confusion matrix of the linear SVM using cross-validation.

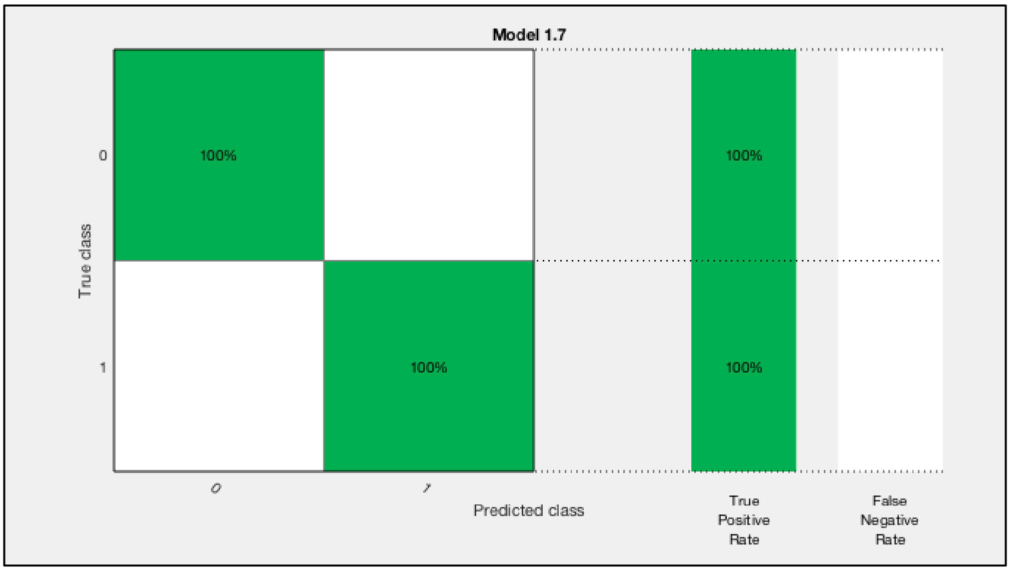

Figure 24: Confusion matrix of the linear SVM model using holdout validation.

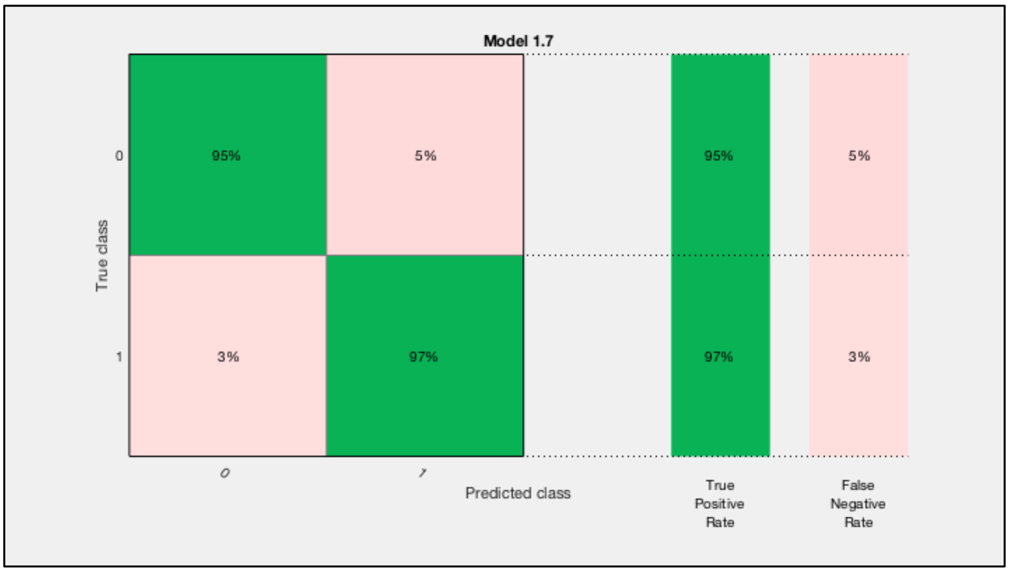

Figure 25: Confusion matrix of the linear SVM model using cross-validation.

On the other hand, for sensor 2 it was found that quadratic SVM and fine gaussian SVM have achieved the highest accuracy percentages using holdout validation and cross-validation. The confusion matrices for both models using holdout and cross-validations are shown in Figure 26, Figure 27, Figure 28, and Figure 29 respectively. After comparing the accuracy results, we can see that the SVM classifier achieved higher accuracy compared to decision trees.

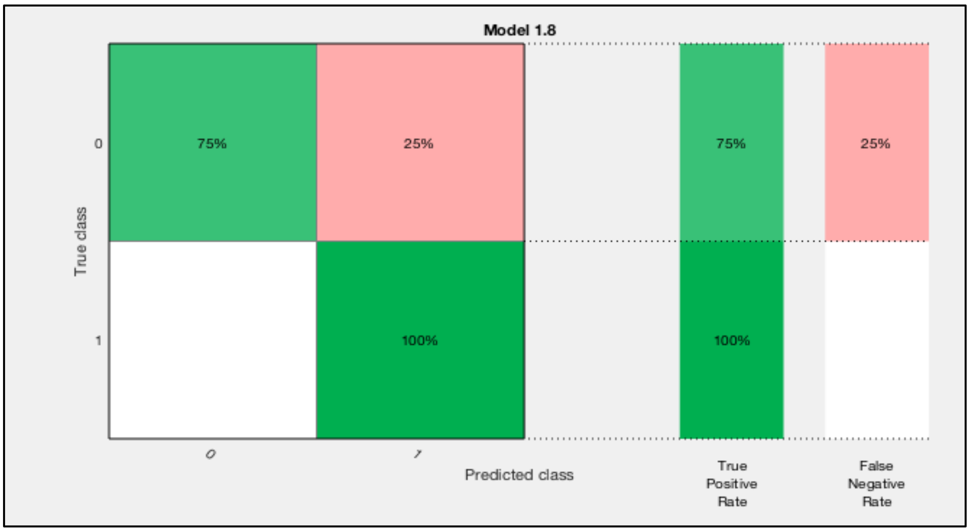

Figure 26: Confusion matrix of the quadratic SVM model using holdout validation.

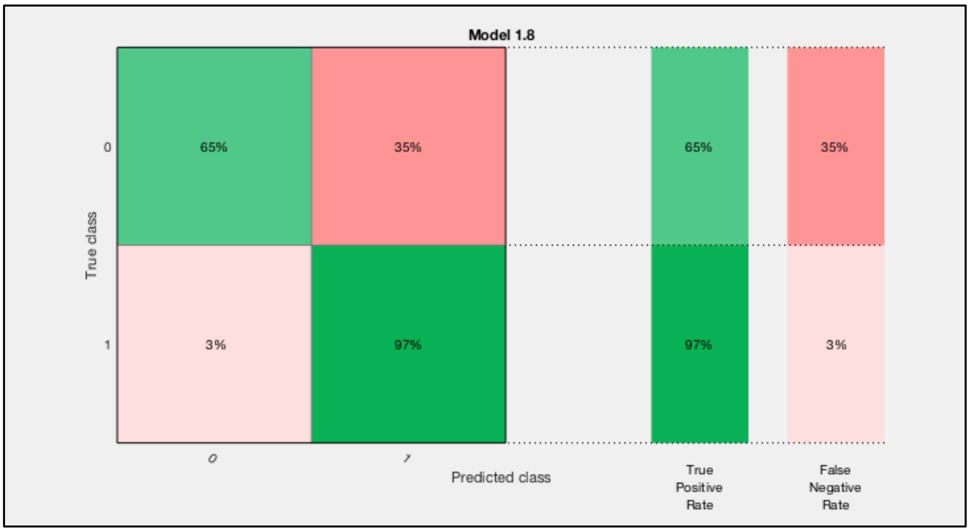

Figure 27: Confusion matrix of the quadratic SVM model using cross-validation.

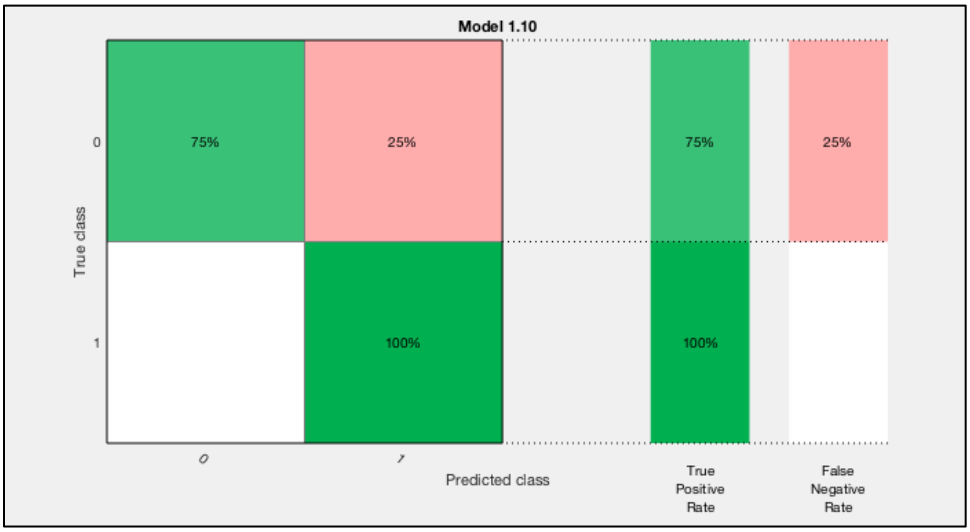

Figure 28: Confusion matrix of fine Gaussian model using holdout validation.

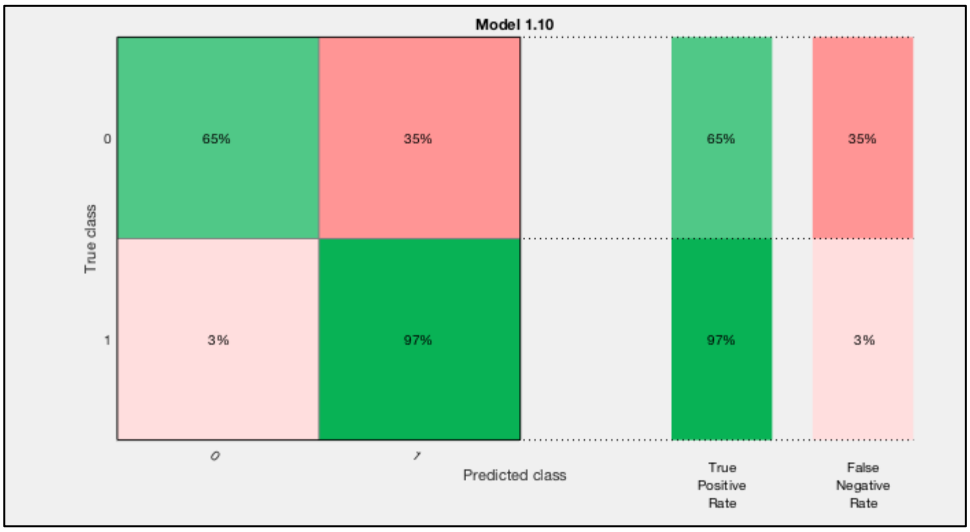

Figure 29: Confusion matrix of fine Gaussian model using cross-validation.

When it comes to comparing holdout validation and cross-validation, cross-validation tends to be better in terms of providing better training to the classifier on multiple training and testing datasets. This method gives a better indication of how the classifier is going to perform on unseen data.

4.10. Economic Feasibility of PdM

IoT concept was applied through using wireless accelerometer sensors, which were connected wirelessly with the data acquisition system.

After we collect the data from the sensors and perform the analysis, using the internet connection will allow us to establish a communication line that will send the data and make it available online which will be monitored continuously by the technicians without the need for them to be presented physically with the equipment.

PdM implementation is associated with some costs and benefits. Costs are divided into Investment Cost (IC), labor, communication (Comm), and Operations and Maintenance (O&M) costs. Investment costs include the acquisition system and software. Benefits, on the other hand, include reduction of opportunity costs, breakdown cost, inventory cost, secondary damages as well as extending the life of the equipment.

4.10.1. Costs. To collect from 0 to 50 points to be measured per month, one maintenance engineer is required [110]. The average salary of a maintenance engineer is AED 69,856 per year [111].

Data acquisition allows measuring an electrical or physical phenomenon such as voltage, current, temperature, pressure, or vibration with a computer. A data acquisition system consists of sensors, measurement hardware, and a computer with programmable software. Its value is around AED 30,000. In terms of communication, internet subscription is required to establish the connection between the different parts of the system which is estimated to be around AED 7,200. One software that can be used for data analysis in MATLAB which has a perpetual license cost of AED 8,632. O&M is estimated at 10% to 15% of the capital cost [110].

4.10.2. Benefits. PdM reduces the number of equipment outages by reducing the number of unplanned stops. Also, machine downtime can be scheduled for the most suitable and inexpensive time. Thus, the availability of hospital equipment increases and its usage as well, so the equipment is more utilized which generates more profit over the saved time. According to the local hospital, the Vitros machine performs around 50 tests per day and the minimum cost per test is around AED 200 which will result in an opportunity cost of AED 10,000 for each reduced breakdown of the machine.

Inventory costs will be reduced since failure can be predicted; the backup materials stored in inventory are reduced as spare parts can be ordered when required. The cost reduction is estimated to be around AED 3,000 [110]. PdM indicates when the machine is about to break and thus it helps in reducing the number of breakdowns as they can be avoided by fixing the problem before it occurs. Therefore, costs for breakdown are reduced. PdM reduces the number of times the machine is disassembled as it is now disassembled only when required. Therefore, the machine lifetime is extended [110]. The use of IoT and PdM can reduce the cost up to 25% by reducing the major failures by up to 50% and extending the life of the equipment up to 36% [112]. So, if the cost per breakdown is around AED 500, after implementing the approach it will be reduced by 25% which is around AED 375. Since the failure is detected in advance, sequential damages are prevented from occurring. For example, the failure of the sample-metering arm can be identified and fixed before other sequential damages occur. According to [110], repairing before machine failure occurs reduces the repair bill by ten times. Based on that, data was collected as shown in Table 13.

Table 13: Annual costs and benefits (AED) of implementing PdM.

Costs	
Labor	69,856
Acquisition system	30,000
Communication	7,200
Software	8,632
O & M cost	3,923
Total	**120,271.35**
Benefits	
# of breakdown/year before predictive	14
# of breakdown/year after predictive	2
Opportunity cost per breakdown	10,000
Opportunity cost savings	120,000
Inventory reduction	3,000
Cost per breakdown	500
Reduced breakdown cost	375
Total	**123,375**

4.10.3. Cash Flows. The cash flow (CF) calculations were performed based on the collected data described above. Also, the following inflation rate [113], Minimum Attractive Rate of Return (MARR) and Value-Added Tax (VAT) [114] were considered based on UAE economics as shown in Table 14.

Table 14: UAE economic rates.

Economic parameters	Rate
Inflation Rate	2.20%
MARR	8%
VAT %	5%

Accordingly, Table 15 below shows the cash flow calculations over 11 years through which the Net Present Value (NPV) was calculated.

Table 15: CF and NPV of PdM.

Year	IC	Labor	Comm.	O&M cost	Total costs	Total savings	Net CF
0	38,632				38,632		(38,632)
1		74,962	7,726	4,918	87,607	132,394	44,787
2		76,612	7,896	5,026	89,534	135,306	45,772
3		78,297	8,070	5,137	91,504	138,283	46,779
4		80,020	8,248	5,250	93,517	141,325	47,808
5		81,780	8,429	5,366	95,575	144,435	48,860
6		83,579	8,614	5,484	97,677	147,612	49,935
7		85,418	8,804	5,604	99,826	150,860	51,033
8		87,297	8,998	5,728	102,022	154,178	52,156
9		89,218	9,196	5,854	104,267	157,570	53,304
10		91,181	9,398	5,982	106,561	161,037	54,476
11		93,186	9,605	6,114	108,905	164,580	55,675
NPV: AED 312,806.49							

The Net Present Value (NPV) of implementing PdM is AED 312,806.49 after 11 years of use. Since the NPV value is positive, then it yields that the projected earnings generated exceed the anticipated costs. Therefore, PdM implementation is expected to be profitable and it is advisable to invest in.

4.10.4. Payback period. The PdM project payback period is 1 year as shown in Table 16 and Figure 30, where the cumulative cash flow becomes positive with a value of AED 6,155.

Therefore, the management if decided to implement the PdM project should keep the project running for more than 1 year to acquire more positive CF.

Table 16: CF of PdM.

Year	Net CF	Cumulative CF
-	(38,632)	(38,632)
1	44,787	6,155
2	45,772	51,927
3	46,779	98,705
4	47,808	146,514
5	48,860	195,373
6	49,935	245,308
7	51,033	296,342
8	52,156	348,498
9	53,304	401,801
10	54,476	456,277
11	55,675	511,952

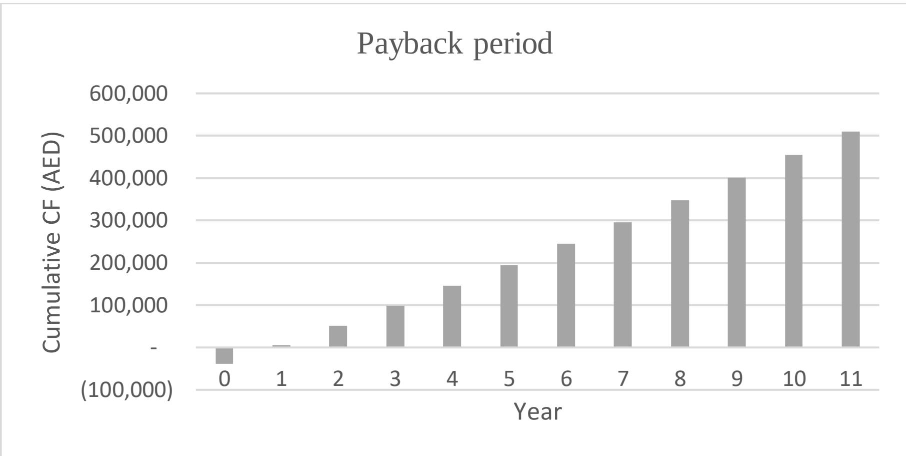

Figure 30: Cumulative CF for PdM.

Considering the reliability of the IoT system, in terms of the availability of the network connection, we have two different aspects to be discussed; the first one is when we are having a single node sensor failure, in this case, we can introduce an architecture where we can add a backup node which will be placed randomly, and when one of the nodes dies it checks all the backup nodes available and selects the node which is at the nearest distance of the faulty or failed node. Moving on to the second aspect, where a whole network failure occurs, we may need a local processor close to the machines and a remote one. The remote will collect data from all machines and process it (sample size maximization), while the local server will be used in emergencies.

Chapter 5. Conclusion and Future Work

In this thesis, the issue of lacking the implementation of the predictive maintenance (PdM) strategy along with Internet of Things (IoT) technology in healthcare industry was addressed to show how the efficient use of such approach can result in many benefits that will be reflected in the total resources of the different industries in general and the healthcare industry in specific. In addition to increasing the system's reliability especially in critical departments, implementing the PdM strategy will be a revolutionary breakthrough in the healthcare industry; not only in providing maintenance to the medical equipment but also in restricting the undesired growth of errors that normally occur by following a time-based or a failure-based strategy, and eventually leads to a complete malfunction of the equipment. Despite the challenges that were faced to carry out this work, the impact that will be gained if this approach is applied was motivating to go through hard times and especially after contacting some well-known companies like GE, and finding out that they are moving towards applying the proposed approach worldwide.

In this work, an IoT-based PdM methodology that can be applied to any medical equipment was formed and applied on Vitros machine in order to achieve the objective of fault diagnosis. After studying the equipment maintenance logs and performing failure criticality assessments, the most critical failures were determined and ranked based on their Risk Priority Number (RPN). Next, the part of interest was simulated in one of the university labs for the purpose of data collection, classification and modelling using the most common machine learning tools. Finally, the economic feasibility of the proposed approach was studied and results indicated that such strategy is worth investing in.

As for the future work, the proposed methodology that have been discussed previously can be applied on more failure modes and other medical machines as well, to improve the quality of services, patients' safety, and reduce the associated risks and costs due to sudden failures.

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Vita

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