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Predictive Maintenance (PdM) Structure Using Internet of Things (IoT) for Mechanical Equipment Used into Hospitals in Rwanda

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Abstract: The success of all industries relates to attaining the satisfaction to clients with a high level of services and productivity. The success main factor depends on the extent of maintaining their equipment. To date, the Rwandan hospitals that always have a long queue of patients that are waiting for service perform a repair after failure as common maintenance practice that may involve unplanned resources, cost, time, and completely or partially interrupt the remaining hospital activities. Aiming to reduce unplanned equipment downtime and increase their reliability, this paper proposes the Predictive Maintenance (PdM) structure while using Internet of Things (IoT) in order to predict early failure before it happens for mechanical equipment that is used in Rwandan hospitals. Because prediction relies on data, the structure design consists of a simplest developed real time data collector prototype with the purpose of collecting real time data for predictive model construction and equipment health status classification. The real time data in the form of time series have been collected from selected equipment components in King Faisal Hospital and then later used to build a proposed predictive time series model to be employed in proposed structure. The Long Short Term Memory (LSTM) Neural Network model is used to learn data and perform with an accuracy of 90% and 96% to different two selected components.

Keywords: Predictive Maintenance (PdM); Internet of Things (IoT); equipment; components; monitoring; reliability; failure

1. Introduction

The success of industries relies on the level of production and level of services to satisfy their clients. The main factor in improved productivity is the effective maintenance of their equipment. Among medium and small industries, the medical industry, with its mandate to save human being life, is today experiencing an increase in chronic diseases that infers a high demand of healthcare to be efficient and is authoritative in keeping a high level of their equipment reliability through severe maintenance programs.

Looking to the few numbers of referral hospitals in Rwanda that have not yet adopted a new technology of virtual patient's health monitoring due to the available resources [1], hospitals do always have a long queue of people looking for diagnostics and treatment. In order to satisfy the patients through effective healthcare services delivery, medical equipment plays a big impact not only to patients, but also to the core business success [2]. Accordingly, there is a growing need for maintenance supervision programs in order to minimize unscheduled downtimes.

Unlike the equipment used in the diagnosis of diseases and treatment of patients commonly called biomedical equipment [3,4] which are mainly maintained by expatriate companies, there are obligatory mechanical equipment that provide secondary supports and much necessary capabilities to these biomedical equipment. Like biomedical equipment, this category requires large capital investment to hospital and, for their maintenance, whether new or aged among them involve cost, time, and effort to maintain.

To date, repair after failure is common practice in this equipment due to the fact that they fail without any notification to the maintenance team; hence, fault detection and unplanned maintenance works can completely or partially interrupt the remaining hospital activities. Moreover, their unplanned downtime may even lead to considerably worse incidents [5], including patient death.

Coping with the technology, with the aim to increase equipment lifetime, availability, reliability, and reduce downtime, unnecessary preventive inspections, maintenance time, and untimely pressure on the maintenance team as well as associated costs, the maintenance team requires real time conditional based evidence for effective maintenance [6,7].

Motivated by the aforementioned matters, noticing a gap in the adoption of existing predictive maintenance architecture for these types of equipment due to different mechanical behaviors from one to another and the nonexistence of historical or real time performance data, this work:

- proposes the Predictive Maintenance (PdM) Structure using Internet of things (IoT) for mechanical equipment used into Rwandan hospitals; and,
- describes the whole process, from real data collector development, real data gathering, up to the fault detection sights from equipment's components before they fail.

The data that were used to build a predictive model were gathered in King Faisal Hospital to two critical components of large hospital autoclave sterilizer with a built in electric steam generator that uses steam as a sterilization agent. Long Short Time Memory (LSTM) Neural Networks was adopted to be suitable model for predicting the physical performance of two selected components with a fitting confidence of 90% and 96%, respectively, by mapping the model fitting parameters.

The remaining part of this paper is structured, as follows: Section 2 introduces an overview of the predictive maintenance evolution, followed by Section 3, which summarizes the role of Internet of Things in predictive maintenance and highlights some previous works. Section 4 describes the used methodology and selected materials in order to develop a prototype that resulted in the proposed overall PdM structure that was powered by IoT in Section 5 and the experiment results presented in Section 6. Finally, Section 7 concludes the study.

2. Predictive Maintenance Overview

Throughout the past decades, according to the technology improvement, the manufacturing industry was also developing from one generation to another [8–11]. Figure 1 shows the evolution in maintenance techniques and objectives for implanting a certain level of intelligence into equipment and systems. When considering the past literature and reflection of industrial live out [9,12–15], maintenance has been considered as the main factor in running a sustainable industrial business by optimizing the entire lifecycle of the entities from beginning to end of their lives. Maintenance has drastically transformed in compliance with the technology requirements and market demands.

In the fourth industrial revolution, the IoT took manufacturing to the next level, commonly known as industry 4.0, which is able to compensate the older approaches by enabling maximizing the useful life of equipment [11,16–19] through real time health monitoring. This can be achieved through empowering the automated and digitized monitoring process by using integrated electronics, information technology, and standards protocols capabilities to smart systems [20–24]. The term "smart" infers the capability of an object to flexibly, effectively, and safely collaborate with another object in order to share information that is allied to the adjacent surroundings.

In order to meet the customer demand and cope with new technology, the organizations that utilize this type of equipment also need to adopt new technology to step up and maintain their equipment. Even though the maintenance techniques revolve from one level to another according to the evolution in technology, each level techniques contain different activities to keep equipment in its best operating status by maximizing their reliability and assuring their availability.

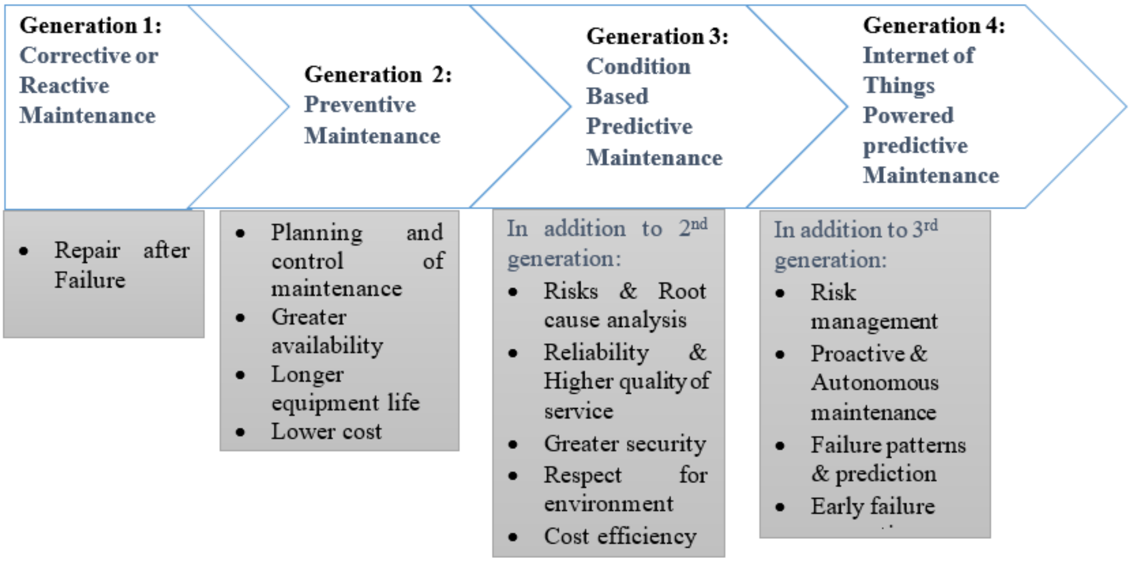

Figure 1. Industrial revolution maintenance techniques and objectives.

For more innovative and competitive workflow, organizations need to continuously access useful data and be able to transmute them into information to adjust their works for better performance. Similarly, today's maintenance technology needs evidence to perform any action on operational equipment. The data from such equipment are crucial and the powerful evidence regarding their health status relate to their health trend observing, diagnosis, forecast, and planning for their reliability; hence, deciding on which component to repair or replace and when.

Taking into consideration the cost that is associated to premature replacement and of sudden failure, the plan on spare parts ordering, quantity, and time could be done conveniently. By gathering increased data, the maintenance team shall be informed on cheap solutions that lead to improved reliability, lower downtime, rarer coincidences, and failures.

3. Internet of Things in Predictive Maintenance

Converging the internet and sensing network technology, after the introduction of Radio Frequency Identification and the Wireless Sensor Networks, the IoT concept has been growing and attracting both in industries and academia since 2000, with the goal of connecting distant remote objects (anything or anyone) at any time in any place by involving different hardware devices, software, and communication capability in order to make any object intelligent, so that they can communicate virtually, regardless of physical location [25–28].

The IoT ability to connect physical objects and allow them to share information through the internet may facilitate collecting a great amount of data that are the powerful strength for the success of any business and future prediction [29,30]. In the maintenance world, embedded hardware that is made up by sensors and other smart devices powered by IoT is today reshaping the industrial and manufacturing maintenance processes [31,32].

The internal equipment outfit is generally unobservable; thus, regular planned preventive maintenance do not provide enough or clear information involving the equipment status to maintainers, when it is operating without any physical symptom to depreciation, it is not practically easy to identify whether there is any root to cause future defect. Consequently, the routine schedule is retained and sudden downtime may occur at an unexpected time, perhaps even during a heavy works period.

The equipment gradually degrades overtime before reaching a complete collapse [33]. The insufficient maintenance accuracy of asset's conditions results in a thorough deterioration that reflect in service deficiency, clients' appointments postponement, and dismay while waiting for the procurement of new spare parts or equipment replacement that always goes together with an increase in cost demand.

Thus, with the power of IoT, the predictive maintenance approach may be powerful in this game to integrate the direct monitoring of equipment through collecting continuous real time data from its health physical parameters.

Late literature reviewed the IoT relevant concepts, technologies, architectures, services, applications, and business models [26,29,31,34]. Among the applications, IoT offers predictive maintenance solutions in different scenarios from different industries; among them are healthcare industry [2,35–37], energy [38–44], and industrial automation and machinery [29,44–72], to which also this work belongs.

The PdM Structure using IoT involves sensors for capturing the continuous real data of highlighted key stress factors that lead to deficiencies, such as vibration, temperature, noise level, pressure, power consumption, etc., and other coupled devices to make an asset visibility to the user by getting continuous sights on their health changes.

The predictive maintenance using IoT cannot be efficient without advanced data analytics tools and machine learning techniques [73–75] that use historical performance data to discover the remarkable insights that are linked to the equipment performance, detect anomalies in variances, discover patterns or warning signals that could be a sign of impending failure, and from them:

- estimate when the asset is probable to fail;
- classify the equipment's part to cause the failure; and,
- provides suggestions on the most effective period of time to perform preventive actions.

Despite a thorough investigation of the denoted benefits, the predictive maintenance adoption by hospitals in Rwanda among other small- and medium-sized companies is still not mature due to differing reasons, either because of the historical data unavailability, trustless of the technology, or associated initial cost. Mainly, they need evidence [8,21,76–79] to prove that the early fault detection enables them to:

- rake early and necessary corrective measures;
- intervene in effective manner, minimize unplanned outage, avoid unnecessary and improper works, and minimize premature replacement; and thus,
- save time and resources, reduce valuable figure of maintenance costs, increase reliability and productivity to businesses' turnover, and extends the lifetime of aging assets.

4. PdM Structure Development Methodology

The health monitoring of equipment's components helps in detecting premature faults. Starting a PdM structure that is powered by IoT requires integrating a new and separate independent structure built with the ability to collect data, process them, and make data perceptions sharing across existing systems [80].

The preliminary works before stating the construction of system for predicting the forthcoming faults, including the different steps:

- highlighting the equipment in query and conducting its operational assessment;
- collecting its data from maintenance history to discover and describe what type of faults mostly make it traumatized, their impact to the system, and how they were identified; and,
- basing on acquired information, highlight the critical components and their physical parameters to be monitored as well as the needed materials.

The PdM requires the embedded system that is powered by the IoT capabilities to keep spotting the continuous streamed sensors data, various linked hardware (microcontroller,sensors, communication module) to process data, as well as to provide feedback in continuous manner [76,81]. Figure 2 shows the process steps in constructing a supervised predictive maintenance structure up to early impending failures detection and providing insights regarding equipment life status.

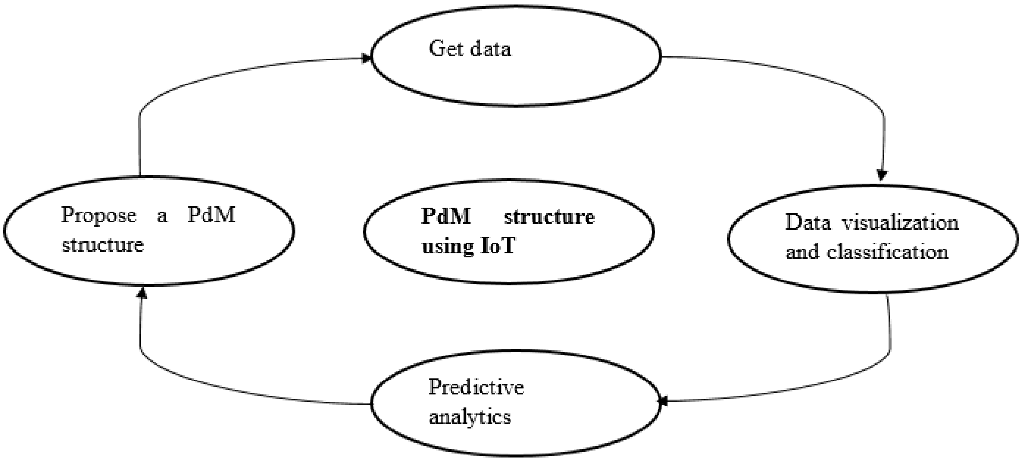

Figure 2. Methodological steps to construct a Predictive Maintenance (PdM) Structure using Internet of Things (IoT).

4.1. Get Data

The selection of suitable technology and linked protocols to obtain real and continuous data relies the environment of targeted equipment that helps to define which type of data are to be captured, the amount of data, data format, data transmission protocol, transmission rate, as well as the needed materials for constructing a complete architecture suitable for queried solution. All equipment do not suit the same monitoring system, due to their normal characteristics and operation. Thus, the selection of targeted equipment could be done prior to designing the data collection tool.

4.1.1. Equipment and Critical Parts Selection

The hospital industry, like other industries, uses mechanical equipment and these differnet types of equipment serve the whole community. The selection of the equipment relates to its importance in the industry.

For this study, we investigated one amongst the most critical hospital mechanical machinery. An autoclave sterilizer is mandatory in hospital with the aim of avoiding the possibility of pathogen transmission from the medical object to patient or to hospital staff and environmental contamination. This machine uses a saturated steam to produce high temperature and pressure as sterilization agent. Sterilization serves to destroy pathogenic microorganism that could lead to infection [82–84].

Some authors [60,61,85,86] focused on sterilization chamber regulation and steam quality, but did not consider the main mechanical parts to generate the required agent for successful sterilization. This machine is structurally complex; consequently, its maintenance is stressful and it requires reserving their spare parts in stock in order to avoid any kind of its component failure that may lead to breakdown its operation.

Among its critical parts, there is a steam generator that is made up by water tank and heaters in otder to generate a saturated steam, which is the main agent of sterilization. Once one of the heaters slows down, the sterilization is affected. There are also pumps that are devices that move fluids by mechanical force. Pumps are also extensively used for small to large scale appliances in both domestic, enterprise, organization, and manufacturing industry appliances [62,63].

Pumps worse behaviors may cause the most amount of failure not only of itself, but of the whole critical system. For the autoclave, pumps occupy considerable importance in its normal working process, as any kind of defect could cause a total downtime of the whole system, which may result in expensive complications.

Autoclave presents two centrifuge pumps, namely water and vacuum pumps with the same mechanical and physical parameters. Water pumps serve to supply water to the steam generator, whereas vacuum pumps are used in order to evacuate air bulbs and moisture on the load in sterilization chamber to continually keep the effective vacuum condition for successful sterilization.

Pumping system contains different components, such as a pump itself, which feeds kinetic energy to fluid, a motor that supplies the mechanical force to pump for its working, piping, valves, measuring equipment, and beneficiary equipment. Any stress from one of these components results in pump behavior change, which is then transferred to the coupled motor.

Referring to literature, different researches put emphasis on the fault diagnosis of the pumps by analyzing changes in its associated motor quantities [49,51,59,64–68,71,72], but did not consider the pumps as an individual unit that borrows stresses from its own inefficient operation or surrounded components.

The first pumps defects symptoms, such as bearing failure, misalignment, bed failure, and associated motor failure, which lead to a rise in their operating temperature [63,69], which, in turn, gradually shortens its life cycle and efficiency. In normal condition, pumps keep their environment temperature and, for any change in temperature increase, the inner temperature is directly propagated to its metallic housing and then to a coupled motor.

The data gathering and processing experiment of this study focus on steam generator and pumps temperature as main physical behavior for detectinf failure. The collected data were used in constructing a predictive model that can learn the real time data taken with a small interval of time and classifying the components' health status.

4.1.2. Requirement for Data Collector Device Development

Data collection is a pillar step in predictive maintenance. The objective of this stage is to develop the IoT based time series data collection structure that allows for interaction between smartened physical object and virtual organization applications. Data collection can be subdivided into two main parts, namely maintenance history data collection provided by maintenance team and sensors' raw data collection gathered while using the developed data collector. From maintenance history data, you learn the equipment functionality and its maintenance history. This phase of knowing equipment gives an idea of which important components should be monitored and which monitoring is needed for specific possible faults.

In our experiment, we developed a data collector prototype in Section 5.1. The temperature was highlighted as a major stress symptom to be monitored on the identified components. The Negative Temperature Coefficient (NTC) thermistor [87–89], which is a thermal resistor that changes radically its resistance with temperature over exceedingly accuracy, was used to measure temperature.

4.2. Data Visualization and Classification

With purpose of showing the component's health status, the collected data should be visualized and classified into categories, depending on their changes versus a component health performance phases. This phase requires the equipment performance bulletin that is provided by manufacturer to know the normal working parameters of each component, past historical maintenance data, conducting a deep supervision of operating equipment to detect what happened when the collected data became different, as well as exploratory data analysis. For final reporting, the health status categories must be defined before the deployment of the model to the application.

4.3. Predictive Analytics

The aim of this phase, as per the process shown in Figure 3, is to identify the appropriate predictive machine learning model for queried application by processing the raw historical data from sensors that have been kept for a certain period up to the chosen fitting model.

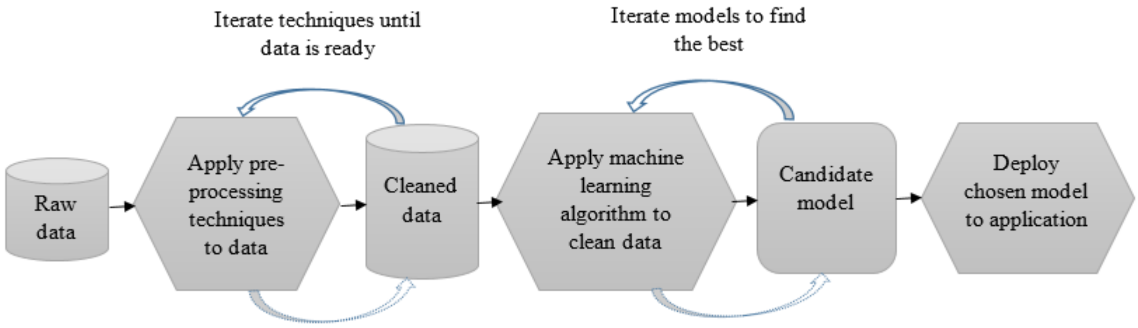

Figure 3. Predictive analytics and modeling process.

Data processing involves the understanding of data, cleaning data from outliers and other artifacts. This might lead to the easier extraction and selection of valuable information related to the parameter being monitored. The feature extraction focuses on the interesting signals from the preprocessed data that can be the useful indicators for a fault detection and failure point assumption.

Different machine learning models can be trained in order to classify data and provide prediction before the monitored component is likely to oblige repair or replacement. From the literature, traditional time-series techniques, such as Hidden Markov model [90] and Kalman filtering [91], perform the prediction by detecting variations in data distribution based on predefined sequences, interval of time or distance, as well as thresholds. The main shortcoming of those algorithms is the ability to learn long term dependence for detecting the relation between features in different time series.

Our real time monitoring requires a model with the capability to keep the long time dependence performance data without predefined time steps ahead of time. Thus, the Seasonal Autoregressive Integrated Moving Average (SARIMA) and LSTM models are candidates, where LSTM performed well on our experimental data with a low root mean square error (RMSE) when compared to SARIMA.

The Long Short Term Memory (LSTM) predictive model that was introduced and modified in [92,93] is proposed to this application with the aim of keeping the memories of long past time point to predict the tendency of future behaviors of the equipment.

LSTM is a special type of Recurrent Neural Network (RNN) with a hidden unit that consists of four gates, namely input (i), output (o), forget (f), and update (u), as illustrated in Figure 4. The LSTM unit performs the mathematical Equation (1) to compute Equations (2)–(8), for four different gates with same size, in order to update the next hidden state h_t and cell state and compute an output Y_t at a specific time step t by taking the previous hidden state h_{t-1} and current input x_t, stacking them, and then multiplying them with weight matrix, W, all being triggered by activation functions.

Gates are used in order to update memory cell C_t at time t, with new time step information and forgetting the previous historical data, and then expose part of cell as the hidden state at the next time step.

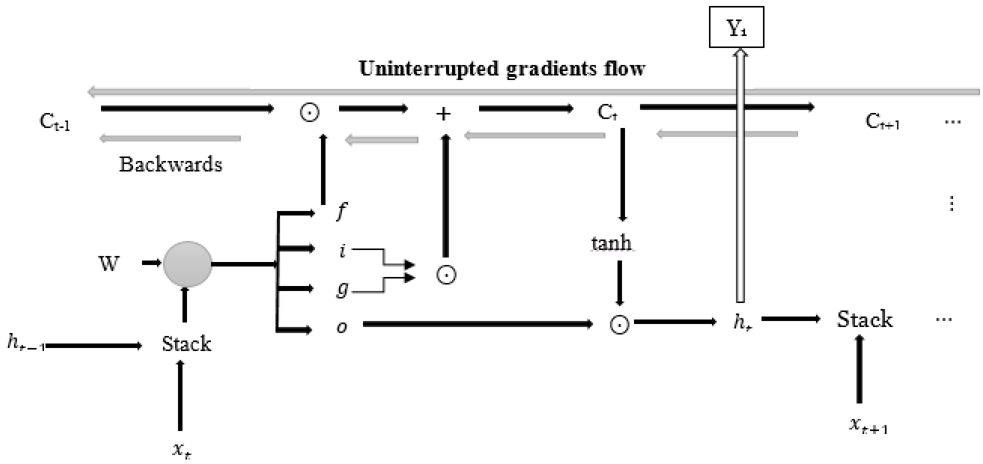

Figure 4. Long Short Time Memory (LSTM) Cell structure.

LSTM Cell function:

$$h_t \begin{pmatrix} i \\ f \\ o \\ u \end{pmatrix} = \begin{pmatrix} \delta \\ \delta \\ \delta \\ \phi \end{pmatrix} W \begin{pmatrix} h_{(t-1)} \\ x_t \end{pmatrix} \tag{1}$$

$$i_t = \delta(W_{x_i} x_t + W_{h_i} h_{t\_1} + b_i) \tag{2}$$

$$f_t = \delta(W_{x_f} x_t + W_{h_f} h_{t\_1} + b_f) \tag{3}$$

$$o_t = \delta(W_{x_o} x_t + W_{h_o} h_{t\_1} + b_o) \tag{4}$$

$$u_t = \phi(W_{x_u} x_t + W_{h_u} h_{t\_1} + b_u) \tag{5}$$

$$C_t = f_t \odot C_{t\_1} + i \odot u \tag{6}$$

$$h_t = o_t \odot tanh(C_{t\_1}) \tag{7}$$

$$Y_t = W_{h_o} h_t + b_o \tag{8}$$

δ denotes an application of the sigmoid logistic activation function, ϕ denotes an elementwise application of hyperbolic tangent (tanh) activation function, x_t represents an input vector to model, h_{t-1} is the activation delivered in the previous sequence step, and C_t denotes the value of LSTM memory cell; all at the $t^t h$ time step and h_t is the probability distribution result function at a given step, which is also the next hidden state. W_x and W_h are the input and hidden connection weight matrices to gates and b is the bias vectors employed to create connection between input layer, output layer, and memory block. $\odot$ is the entrywise multiplication. Additionally, Y_t is the predicted label at each time step.

5. Proposed Predictive Maintenance (PdM) Structure Using Internet of Things (IoT)

The PdM structure depends on the queried environment as well as a predictive analytics tool to discover the remarkable insights. Because the data type leads the remaining parts of the prediction: before proposing the PdM structure using IoT, we have developed a data collector prototype to help us obtain real time data in order to learn a predictive model to be used in our proposed structure.

5.1. Generating Data for Predictive Model Construction

Noticing the unavailability of the equipment performance data, we developed a data collector that was used to collect the real time data to be used in the development of predictive analytics model. The collected data helped to observe data changes versus components health performance with the purpose of classifying the operating component health status. Figure 5 illustrates the main components schematic of the data collector that was used to gather and transmit data.

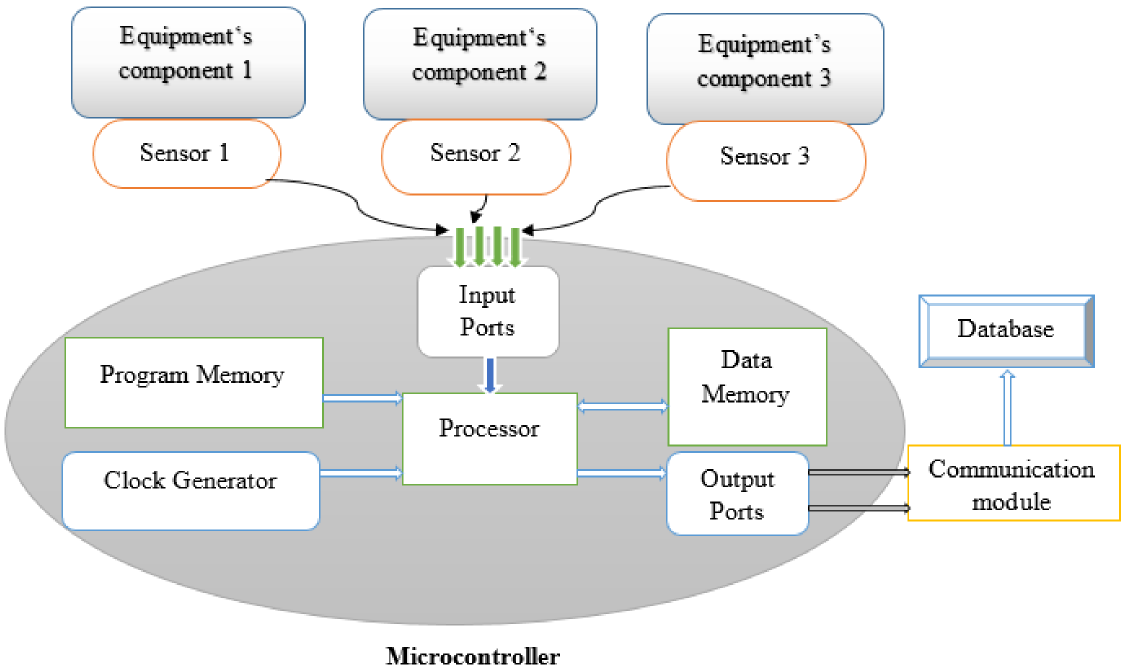

Figure 5. Data collector prototype main components.

For our experiment, temperature was highlighted as main defect symptom of the selected equipment's components. The developed embedded device was made up of temperature sensors for collecting real time temperature, a microcontroller for processing data, and a communication module for transmitting data to the database.

5.1.1. Sensors

The real time data might be collected while using specific sensors. In our experiment, due to the range of temperature for targeted components, we selected NTC thermistors with the capability to operate over −40 °C to +300 °C. Figure 6 illustrates the data collector details, whereas Figure 7 shows the developed device that was connected to the equipment.

Equipment is not used all of the time and its operating time keeps changing, depending on the available workload. Closer readings from sensor may provide clear performance sights even during short operating period of time. We made sensors to provide time series data every 30 s.

5.1.2. Microcontroller

The microcontroller could be chosen, depending on the data processing activities. The Arduino Uno board [94] was used due to the fact that required data were to train and test the model to be used as a predictive tool, when considering the hardware simplicity and narrowing its associated cost. It is based on the microcontroller known as ATmega 328. It has a set of analog/digital input/output pins and communication interfaces that help the user to connect different sensors and communication module. Figure 8 shows the flowchart of the program that was running on Arduino Uno microcontroller board.

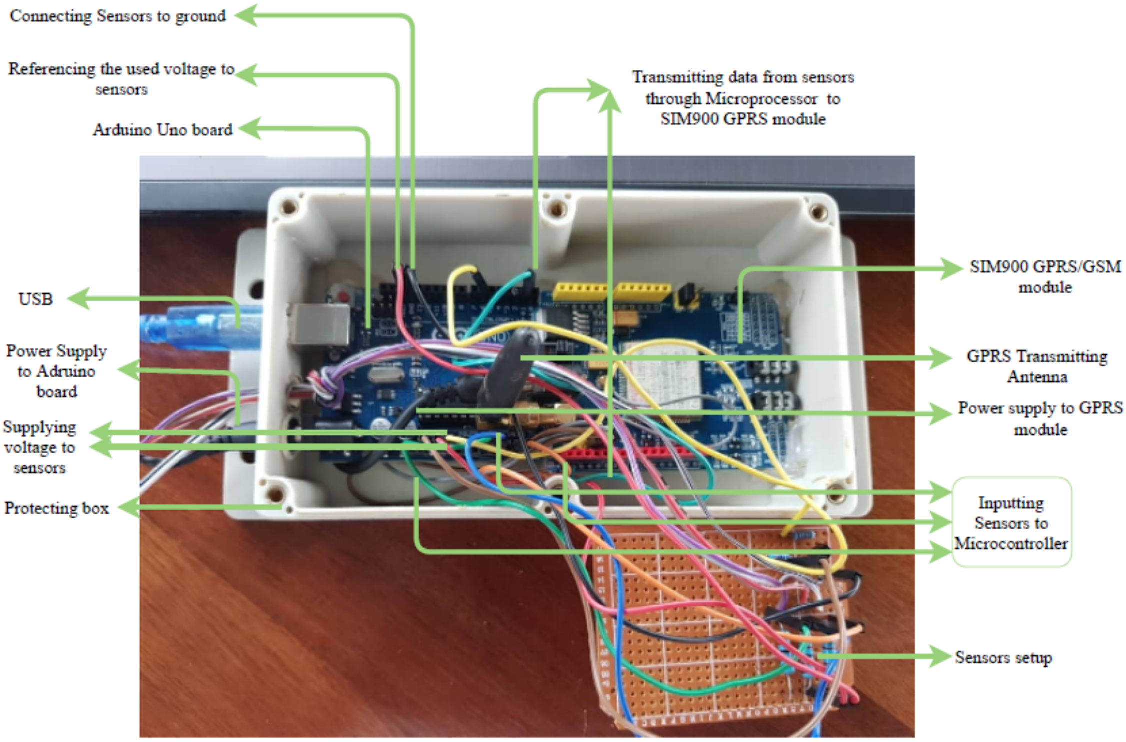

Figure 6. Embedded Data collector device in box.

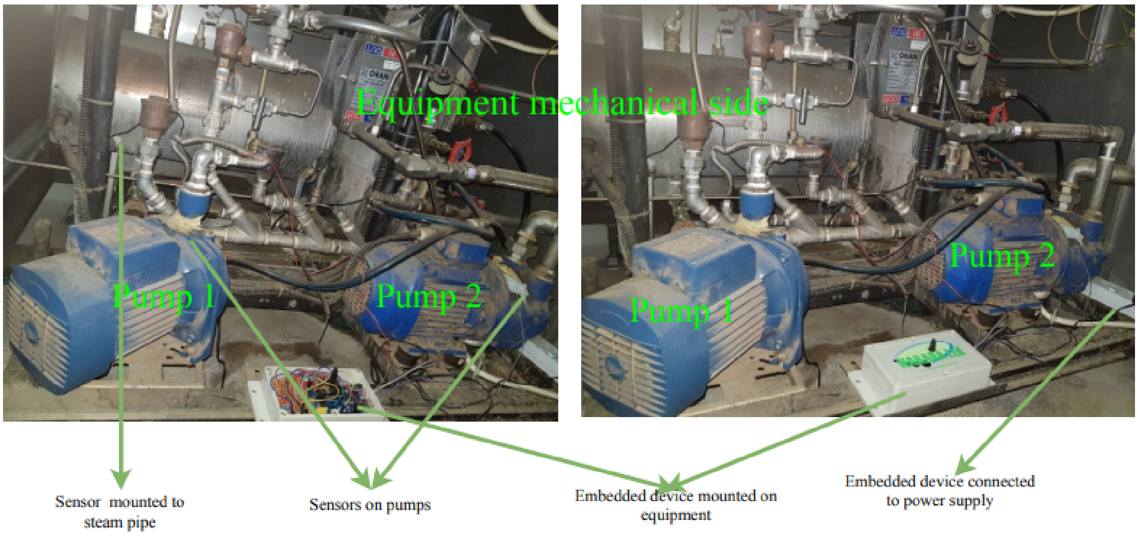

Figure 7. Developed data collector connected on equipment's components.

The program running into the microcontroller to collect and transmit the data is performed through five phases:

1. Ports for sensors and communication module are initialized and configured.
2. Read voltage sensors' data corresponding to the thermistor resistance.
3. Convert voltage into the temperature.
4. Try to connect to the GSM network
5. If the microcontroller is connected to the GSM network, the data are sent to a remote database. Otherwise, the microcontroller keeps trying to connect to the GSM network

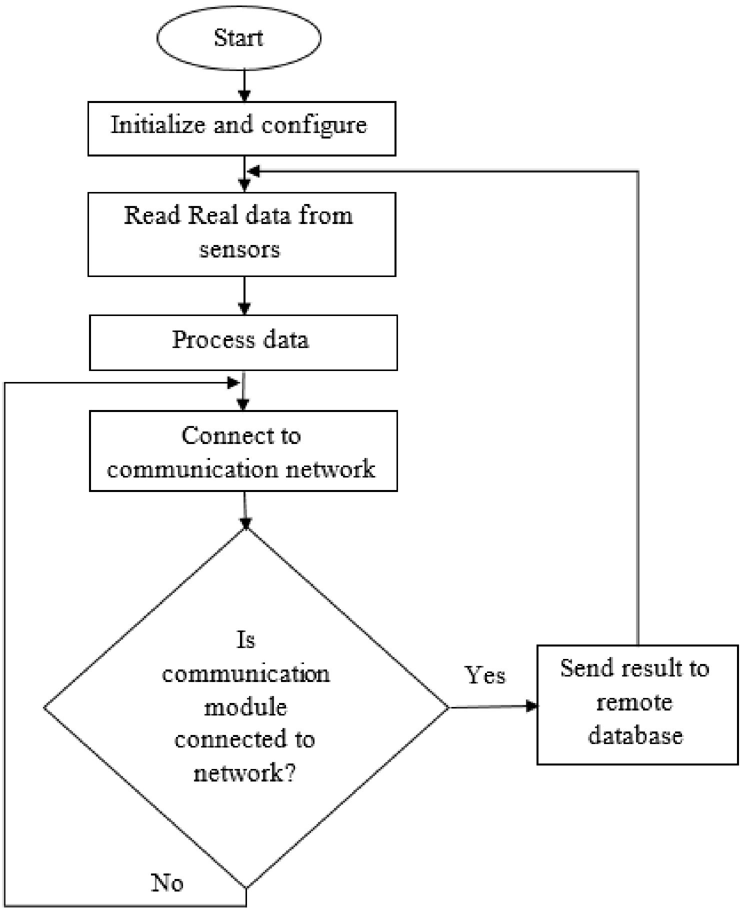

Figure 8. Program running into Arduino Uno.

5.1.3. Communication Module

The Microcontroller output is fed to a communication module. This requires the data transmission setup that may increase the implementation cost. Basing on the available infrastructure, SIM 900 GSM/GPRS (Global System for Mobile/General Packet Radio Service) [95] was used to act as a gateway and enable data transfer to the database through internet via the GSM network.

5.1.4. Database

The real time series data could be saved on the device if it has enough memory or on a remote database. For our experiment, the remote database was used to keep collected data. Database data will be used for predictive model construction.

5.2. Proposed PdM Structure Using IoT

Referring to the late studies and proposed architecture [28,29,70,77], the proposed PdM structure using IoT is presented by different interconnected components, as shown by the block diagram in Figure 9.

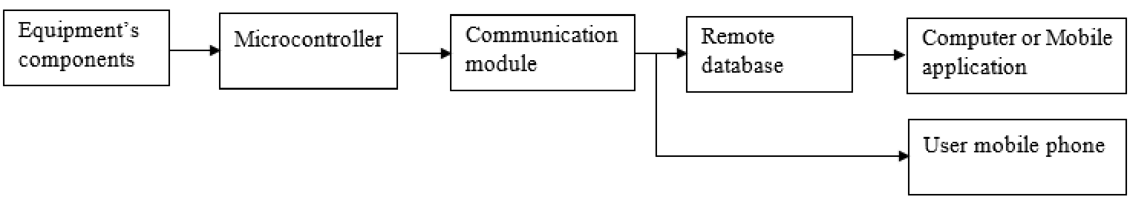

Figure 9. Proposed PdM Structure bloc diagram.

Basing on each component role, the first two components must be settled together, as they serve for data gathering and processing. The communication module transmits data to a remote database from where the user can remotely obtain information through a computer or mobile application. At the same time, a Short Messaging System (sms) may be sent to the user in case of critical condition. The detailed proposed PdM structure illustrated in Figure 10 is presented into three main interdependent parts, which are:

- Data acquisition, processing, and analytics.
- Results transmission.
- Application.

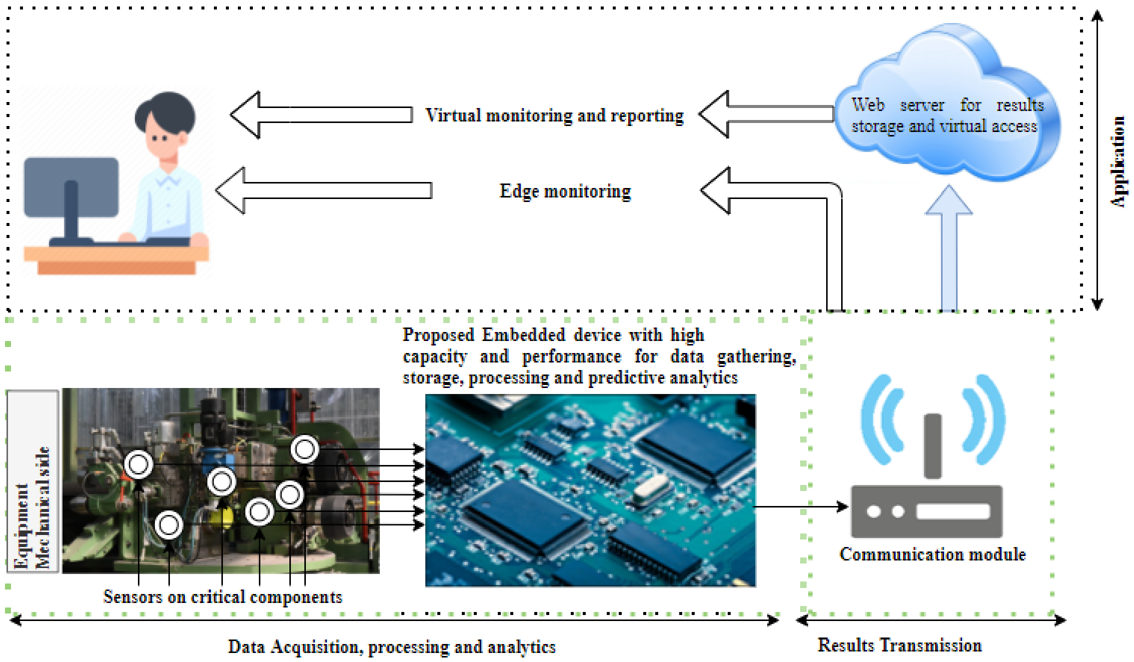

Figure 10. Proposed PdM structure using IoT.

5.2.1. Data Acquisition, Processing and Analytics

It is made up by sensors that are installed on the equipment components, different electronic devices, and a microcontroller that is able to convert and manipulate data based on the purpose of its custom application. With purpose of data processing and predictive analytics at edge, microcontroller might have greater capacity and performance than Arduino Uno board which was used to collect data for our predictive model construction. Based on the functionality of the equipment and its components basic information, this part involves initializing, configuring, gathering, processing, and analyzing the data.

Sensors should be selected, depending on the physical behaviors to be monitored. With purpose of performing the edge data processing and analytics, the microcontroller might have enough storage capacity to store and process data. Figure 11 shows the program executed by microcontroller of proposed structure.

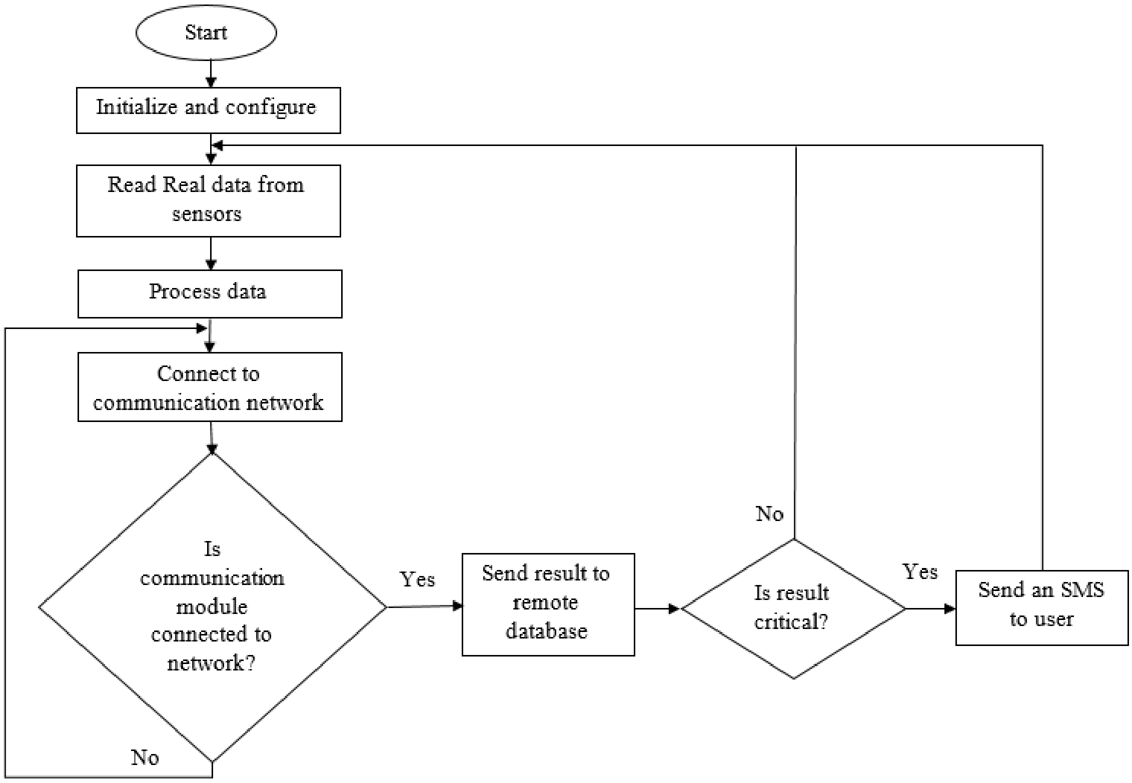

Figure 11. Program running in Microcontroller of the proposed structure.

The program running into microcontroller of proposed PdM structure to collect, process and transmit data is performed through seven phases:

1. Ports for sensors and communication module are initialized and configured.
2. Read the voltage corresponding to received data from sensors.
3. Save received data locally.
4. Saved data are fed to a predictive model for analysis and prediction.
5. Try to connect to GSM network.
6. If microcontroller is connected to GSM network, then the data are sent to remote the database. Otherwise, the microcontroller keeps trying connecting to GSM network.
7. If the result shows an equipment's component critical condition, then a SMS alert is sent to the user.

Based on the real time data, time dependence has great influence on predictive data analytics due to the fact that the present time points are likely to be related to the previous time point or a time point in the long past. Such independency can be helpful in detecting a feature for the present abnormal occurrence, which may be mapped to the previous one.

The prediction of the health status of mechanical equipment relies on the unstable long time dependence performance data. In order to propose the fitting predictive model, the Seasonal Autoregressive Integrated Moving Average (SARIMA) and LSTM models were used to learn and predict from our real time collected data, where LSTM performed well with a low root mean square error (RMSE) of 22.89 and 2.9 when compared to SARIMA, with 29.97 and 3.68 RMSE, respectively, for different component's univariate data.

On top of the predictive model results, the microcontroller could be programmed, depending on results displayed, such as client access limit, reports generation, alerting message, like a short notification message or email sending, customized dashboard outlook, etc., all for the purpose of monitoring.

5.2.2. Results Transmission

The analysed data results will be transmitted to a remote database and a user in the case of alerting results through a communication module that uses internet connection for real time monitoring. In order to avoid an addition cost for new network setup, the existing infrastructures, such as GSM, shall be used.

5.3. The Application

The findings' report shall be transmitted to the maintenance team member for monitoring and to a remote database for storage and virtual access. Users may access the database from anywhere through computer or mobile application. Through monitoring, the generated reports from the streamed data will be processed and analyzed, the early detected faults shall be triggered, and the user may optimize and act on maintenance plan. The reports shall be in a graphic format for the ease of interpretation.

When considering the nature of the maintenance works, maintainers keep moving from one place to another, due to different equipment in different locations, and may be out of network coverage. For them to obtain warning information in a timely manner, the proposed system may send a short notification message to their phones for their actions in the case of equipment component critical condition.

6. Predictive Model Experimental Results

6.1. Data Preprocessing

The real time temperature performance data were collected from three components of the autoclave equipment while using a developed device that is described in Sections 5.1 and saved on a database for a period of three months. The total of 130,140 timesteps data were collected from each component. The collected data were extracted from database, processed using python, and then used to train and test a predictive model that may fit into the proposed structure.

The data distribution from mid-November 2019 up to mid-February 2020 is presented in Figure 12. The distribution of collected data shows that the averaged temperature in November is less when compared to other months. From the partial analysis of the data, we noticed that the collected data from inoperative equipment might mislead the prediction and decided to capture and use data only when the equipment operates.

Among three components, two are similar pumps whose data are shown by Figure 12b,c, which present different changes in physical behaviors. Both data are used in order to train the same model and predict with the aim to check the model performance for different data from similar components. For both data, the performance is same (96%).

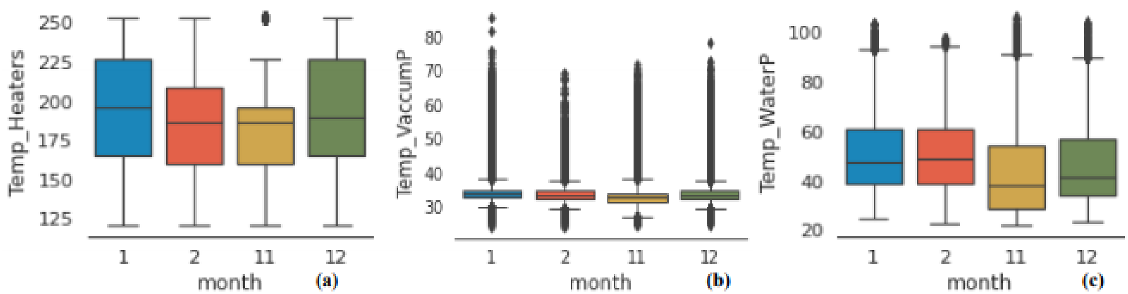

Figure 12. Distribution of collected data. (**a**) represents the data from steam generator, (**b**,**c**) represent the data from two different pumps.

Data preprocessing consists of special values consideration, which involves the dropping of some data that were taken during out serviced equipment to avoid unnecessary long data dispersion. The real timestamps are also converted into datetime format in order to create a suitable time series dataset in Python. We define a function to create a balanced dataset in order to build a relationship between timestep X_i with time dependence t.

Because LSTM acquires a series of past observations to build a function for new input series, our data are sampled into small subsequences in order to comfort the LSTM learning. Each subsequences is made up by a sample of timesteps from which LSTM learns to predict the next time steps. To fix the length of sample, we iterate the process of model training and prediction using different lengths to obtain their optimal number with minimum error. Our minimum model error obtained a sample size of 70 steps.

In order to comply with the time steps LSTM array structure, we transformed our data to be in three dimensional array in the form of [sample, time steps, features]. Prior to starting to learn our model, we randomly split our data into the train dataset, which is indexed to 80%, whereas the remaining 20% were reserved for test dataset.

6.2. Modelling Results

A particular predictive model has to be developed for different components due to the fact that physical behaviors and thresholds differ from one component to another. Two models with slightly different parameters have been constructed while using Keras library [96] in Python through the sequential model Application Programming Interface (API).

Given a sequence of train data x at each time step t; $x_t = (x_1, x_2, \ldots, x_n)$, where $t = 1, 2, \ldots n$ and x is a time step from train data whose arrangement is shown in Figure 13.

0	2019-11-13 15:08:43	84.95	34.39	41.19
1	2019-11-13 15:09:13	90.34	33.98	41.55
2	2019-11-13 15:09:44	80.85	34.32	43.44
3	2019-11-13 15:10:16	82.15	34.18	41.19
4	2019-11-13 15:10:47	84.46	34.18	39.71
5	2019-11-13 15:11:18	82.15	33.98	40.48
6	2019-11-13 15:11:49	83.98	34.79	40.66
7	2019-11-13 15:12:20	83.51	33.98	40.83

130132	2020-02-07 09:23:38	195.81	32.14	51.25
130133	2020-02-07 09:24:14	208.58	32.08	54.42
130134	2020-02-07 09:24:41	208.58	32.02	57.36
130135	2020-02-07 09:25:15	306.64	31.66	59.34
130136	2020-02-07 09:25:48	226.11	32.82	62.53
130137	2020-02-07 09:26:15	208.58	32.32	64.75
130138	2020-02-07 09:26:46	208.58	32.20	67.17
130139	2020-02-07 09:27:18	306.64	32.57	69.29

Figure 13. Imported Data presentation in Python.

The LSTM performance depends on to the hyperparameters turning. To find the optimal parameter values that result in minimum model loss and improve the model efficiency from overfitting phenomena, at the end of each model hyperparameter turning, the created model is evaluated on both the train and test datasets, and the Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) are calculated using Equations (9) and (10), respectively, and the values are saved.

$$MAE = \sum_{t=1}^{n} \frac{1}{n} |Y_t - \hat{Y}_t| \tag{9}$$

$$RMSE = \sum_{t=1}^{n} \sqrt{\frac{1}{n} (Y_t - \hat{Y}_t)^2} \tag{10}$$

where Y_t and $\hat{Y}_t$ are, respectively, the actual and the predicted value by the model corresponding to Y_t at time step t, n is the total number of steps of the test set.

In order to evaluate the model, we iterate the turning different parameters to different values and save the MAE and RMSE scores. By comparing the obtained errors, the minimum model loss that is attained on the hyperparameters values is shown in Table 1.

Table 1. Model parameters optimal values in experiment.

Parameters	Optimal Model Values for Heaters Dataset	Optimal Model Values for Pump Dataset
Train dataset lot	80%	80%
Test dataset lot	20%	20%
Input layer	1	1
LSTM Cells/Units per each	2 cells/50 units per each	1 cell / 100 units
Activation	Rectified Linear Unit (ReLu)	
Dropout wrapper		0.2
Dense Layer	1	1
Optimizer	Adam	Adam
Epoch	20	20
Batch sizer	70	70
Look back window	30	30
Loss function	Mean Squared Error (MSE)	MSE

Table 2 presents the minimum error values as well as model performance accuracy. The test mean absolute error is less than that of training, which is the best for our model.

Table 2. Model performance evaluation values.

Evaluation Factor	First Model for Heaters	Second Model for Pumps
Train Mean Absolute Error	19.699	1.624
Train Root Mean Squared Error	24.895	2.830
Test Mean Absolute Error	17.968	1.598
Test Root Mean Squared Error	22.894	2.900
Coefficient of determination (R^2)	0.755	0.963
Total error loss	0.096	0.04
Accuracy	90.432%	96.0%

Figure 14 shows the training and test loss of our LSTM model at optimal parameter values. We can see that the train and test losses decrease for larger epoch values and that train and test losses both stabilize at closer points. The loss instability in the pump model resulted from data complexity due to the continuous changes of equipment health status.

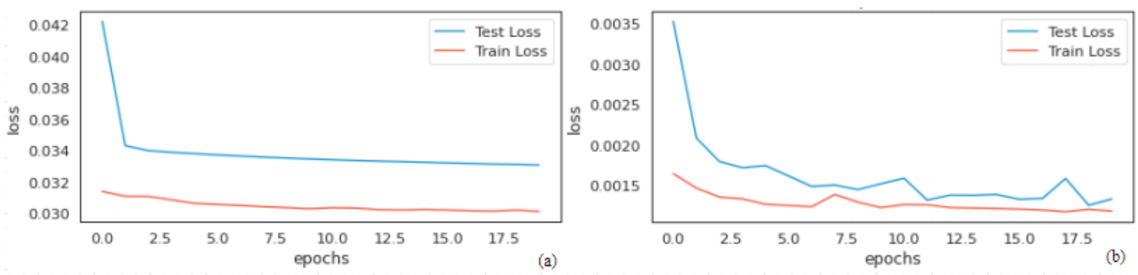

Figure 14. Model loss for (**a**): heaters and (**b**): pump models.

Figure 15 shows the actual and predicted results for both the train and test data. For pumps, the actual and predicted results are closer. A slight fluctuation between the actual and predicted values on pump train data is caused by the dropout regularization that is used to reduce the overfitting phenomenon and prediction error to unseen data. The heaters' dispersion results between actual and predicted points are explained by the higher fluctuations of the real data from component.

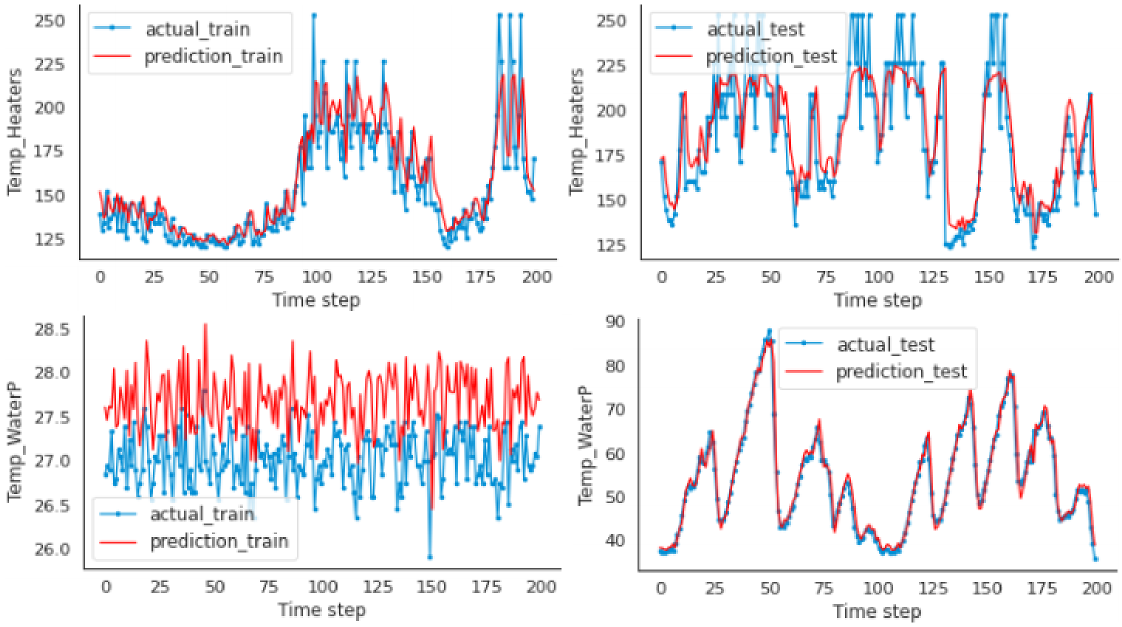

Figure 15. Actual and predicted results for heaters and pumps models.

6.3. Discussion and Future Work

The experimental results show that meaningful real data could only be gathered when equipment operates.

We used our real time data to execute our LSTM algorithm. Based on the calculated performance accuracy with a low training and test MAE and RMSE, as Table 2,

- Our models' accuracy are 90% and 96% on predicting the component temperature.
- Our models do not overfit and the loss is less. We naively conclude that their prediction accuracy are good.
- We recommend LSTM model to be used as predictive model in proposed structure.

Classification of components health status should be done after investigating their operational principals and observing their generated data versus their health change.

Based on the pumps operational specification, past maintenance history, as well as the experimental observation on the machine fluctuation versus the changes in pump's temperature, the temperature working performance range was sub-categorized, relating to related operational health status.

The temperature from steam is irregular time series, due to the fact that it is usually affected by the normal operation of the machine, such as adding cold water into steam generator and automatic regulated heating grasp during operation. Nevertheless, its output temperature may rise and fall in some range along the operation period. In additional, because the change in temperature of steam relates to the temperature change in sterilization room, we have observed 100 sterilization cycles for classifying the range of desirable temperature of the steam.

Table 3 illustrates the operational performance classes with their related temperature range.

Table 3. Component health status thresholds for both pumps and heaters.

Component Health Status	Temperature Range for Pumps	Temperature Range for Heaters
Healthy	Below 40 °C	Above 150 °C
Alerting	41 to 70 °C	141 to 150 °C
Going to collapse	Above 70 °C	Below 140 °C

Based on the highlighted equipment' components health category boundaries, Figure 16 shows the process of achieving the final stage of predictive maintenance.

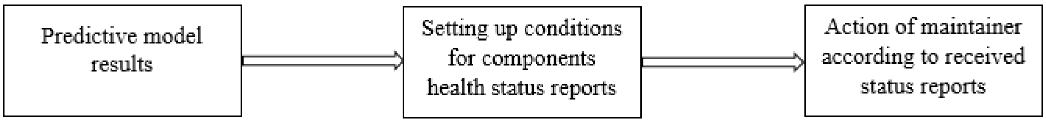

Figure 16. Process to maintenance actions.

On the top of the output layer, every output at current time step will be fed to the defined function with if, elseif, and else condition to read the output and decide based on settled thresholds with the purpose of classifying three health states' labels of the component as Healthy, Alerting, or Going to collapse.

For the alerting system, it is found that, for heaters, temperatures below 150 are only occurring in preheating time that only takes up to five minutes; since the data readings are two per minute, the maximum readings below 150 °C could not go beyond 10 along the whole sterilization cycle. Similarly for pumps, occurrence beyond a healthy status is a good indicator of defect. The maintenance team need to be ready and take actions for maintenance activities, since the 'Alerting' reading is reported and it performs activities as soon as 'Going to collapse' status is reported.

Because a complete sterilization cycle may vary from 45 to 55 min, depending on the load in chamber, the function is defined to conclude the component status after each operation cycle, which is averaged to 50 min. The maintenance team will get an alerting message, since the concluded status is alerted to get ready for the next repair state.

For future work in this field, we note that there are many components on single equipment and different physical parameters on each component that could be assessed in order to create full operation status monitoring of the equipment. Additional works would consider a multivatiable monitoring that combines different component physical parameters. The second aspect would be to create a hybrid model that may compile the results from different components' models, learn them, and then provide the equipment's overall summarized results to the end users.

7. Conclusions

The maintenance of mechanical equipment is a vital aspect in the overall performance of hospitals. Regarding the significance of their availability to the healthcare services in Rwanda, mechanical equipment that is used in hospital requires a real time monitoring system where the health of the equipment is continuously observed and maintained before failure occurs.

In this respect, the structure of PdM Using IoT is proposed. Real time data were collected while using a developed data collector from autoclave equipment three components, of which two are similar at King Faisal Hospital. Prediction was done while using LSTM and performed with an accuracy of 90% and 96% with respect to the components. The prediction of future physical parameters will improve the equipment reliability, availability and reduce downtime.

The scope of this work does not include the maintenance actions priority and scheduling system. Consequently, the study's purpose of creating an intelligent architecture of IoT based PdM structure is attained and it shall be a suitable offer for maintainers' satisfaction and system reliability.

The proposed PdM structure using IoT may also be employed to other industrial equipment with similar physical performance parameters.

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