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RESEARCH ARTICLE

Assessment of IoT-Driven Predictive Maintenance Strategies for Computed Tomography Equipment: A Machine Learning Approach

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ABSTRACT Predictive maintenance (PdM) identifies the equipment conditions and forecasts when maintenance is required to minimize downtime, whis is crucial for medical equipment. This study developed a machine learning-based PdM for a Computed Tomography (CT) scan machine using Internet of Things (IoT) sensors to monitor temperature, humidity, current, radiation, and XY-axis acceleration. Data were collected from January to December 2023 at a hospital in the Klang Valley, Malaysia. The readings were preprocessed to follow a normal distribution, representing the typical working conditions of the machine. Owing to limited faulty condition data, synthetic data were generated by expanding the tails of the data distribution and using a Gaussian noise generator. These synthetic data are vital for training robust machine learning models. An artificial neural network (ANN) was designed to predict the machine's breakdown risk using all sensor parameters as inputs. The ANN model achieved an impressive prediction accuracy of 97.58%, proving its relibility in forecasting breakdowns. The model consistently predicted a high breakdown risk in November 2023, which was confirmed by a repair report that indicating maintenance was required in early December 2023. This study demonstrated that integrating IoT sensors with ANN models can significantly enhance the PdM of medical equipment, reduce downtime, and improve operational efficiency. These promising results suggest the potential application of this approach in other critical medical devices.

INDEX TERMS Predictive maintenance, CT-scan, artificial neural network, machine learning, synthetic data, IoT.

I. INTRODUCTION

The medical industry relies heavily on high-end and complex equipment to provide patients with precise and reliable health care services. Efficient operation of this equipment is crucial for effective diagnosis and treatment. According to World Health Organization (WHO) statistics, over 80% of medical equipment failures are preventable, with inadequate maintenance responsible for approximately 60% of all performance issues [1].

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Predictive maintenance (PdM) identifies equipment conditions and forecasts when maintenance is required. The PdM aims to determine the optimal timing for maintenance actions by utilizing information about the system's current health state and historical maintenance data [2]. In the health industry, Artificial Intelligence (AI) and the Internet of Things (IoT) have been adopted at many stages and across various medical diagnostics, as reviewed in [3] and [4]. This demonstrates the acceptance by medical experts, with AI-based systems being trusted to assist in decision-making.

A case study conducted in [5] observed that Computed Tomography (CT) scan machines are overused, operating

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at double the recommended usage per day, which could lead to machine breakdown. The use of CT has increased rapidly over the years, especially during the pandemic, as shown in Figure 1, owing to the need for rapid COVID-19 detection [6]. Therefore, special maintenance procedures must be implemented to suit the current use of the equipment. Embarking on a special PdM would be appropriate for improving the efficiency, lifespan, and reliability of the equipment given its operation under abnormal conditions owing to community demand. It has also been reported that equipment downtime occurs ten and 15 times per year. Breakdowns increase maintenance costs and reduce community services.

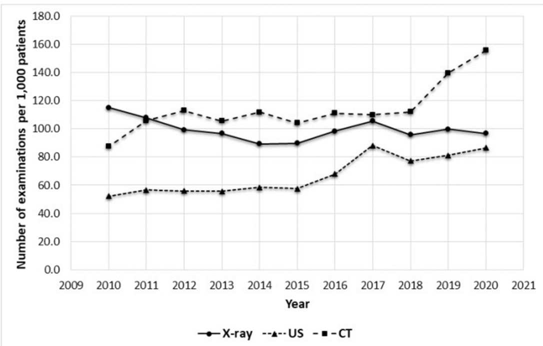

FIGURE 1. Annual change of CT scan machine usage [6].

Different strategies were also proposed in [7] to increase the efficiency of PdM device management. These strategies are tailored to both older and newer high-tech devices. The first strategy considers the results of the performance verification and safety testing, whereas the second strategy follows the manufacturer's recommendations. Currently, CT scan machines in Malaysia are monitored under Planned Preventive Maintenance (PPM) and Corrective Maintenance (CM) [8]. PPM is scheduled maintenance that is normally repeated every six months to maintain the condition of the machine and prevent issues from developing. CM, also known as reactive maintenance, is carried out whenever an issue is found, that is, whether it has led to a breakdown [9].

Implementing PdM in the medical industry poses several challenges, including data privacy concerns, the need for advanced and specialized sensors, and the integration of new systems with the existing healthcare infrastructure [10]. PdM faces significant challenges when real data on normal and abnormal equipment behavior are lacking or scarce, particularly in the case of new systems with no operational experience [11]. Additionally, the implementation of AI in healthcare faces challenges, such as conditions external to the healthcare system, capacity for strategic change management, and the transformation of healthcare professions and practice [12], [13]. Addressing these challenges requires a multifaceted approach that ensures compliance with healthcare regulations and maintains the safety and privacy of patient data, while facilitating strategic change and professional transformation.

Although the PdM in CT scan-machine applications is relatively new, predictive maintenance is widely used in other industries [14]. For example, in the automotive industry, predictive maintenance has been implemented by analyzing the brand and age of the automotive fleet to predict certain failures. Consensus Self-Organized Models (COSMO) accumulate knowledge over time by conducting exploratory searches for internal local signals and comparing them with analogous signals from a group of vehicles performing related tasks. Assuming that most vehicles are in good condition, COSMO anticipates that maintenance is required by monitoring and comparing sensor signals [2].

The predictive maintenance system developed in [15] considers the entire production line based on real-time data collected from IoT sensors deployed in a factory to detect abnormalities in the production line machines. The model estimated the remaining useful time before failure using 101 features fed into a machine-learning (ML) model. The results indicated that ML models based on three ensemble learning algorithms (Random Forest, XGBoost, and Gradient Boosting) outperformed the individual MLP regressor and supported the relevant content and outputs of the prediction model to end users through warnings and visual notifications, depending on user roles and authorizations.

In [16], ML methods such as artificial neural networks (ANN) and support vector machines (SVM) were integrated to provide a better maintenance strategy for building facilities. The proposed data-driven PdM planning framework, based on building information Modelling (BIM) and IoT technologies for facility maintenance management (FMM), consists of an information layer and application layer. The condition of the facility is monitored based on data collected from deployed sensors, including the temperature, pressure, and flow rate, obtained from an IoT sensor network. Sensors monitor the operational conditions of critical components, and trends in sensor data can indicate the frequency of abnormal events and component usage patterns.

Hospitals have invested heavily in advanced medical equipment to ensure accuracy, reliability, and performance standards [17]. Predictive maintenance enhances the reliability of medical equipment, particularly radiation therapy accelerators, by predicting component failures before they cause unscheduled downtime. By employing daily quality assurance treatments, statistical process control methods, and a robust alert system, this model successfully detected 95.6% of the errors introduced during testing [18]. Long-term monitoring is required to confirm the effectiveness of the model in clinical settings. However, the initial results indicate a promising approach to maintain continuous, high-quality patient care. The increasing sophistication of medical technology has significantly enhanced the health of both individuals and society.

The integration of ML algorithms and IoT sensors in PdM involves deploying various sensors to monitor critical parameters such as vibration, temperature, pressure, and velocity, in various applications, such as the semiconductor industry [19]. The data collected from these sensors are processed using sophisticated ML algorithms to detect anomalies and predict potential failures. Algorithms such as Random Forest, SVM, and ANN have shown effectiveness in identifying patterns and predicting maintenance requirement. Figure 2 shows the popularity of the ML model for the PdM [20].

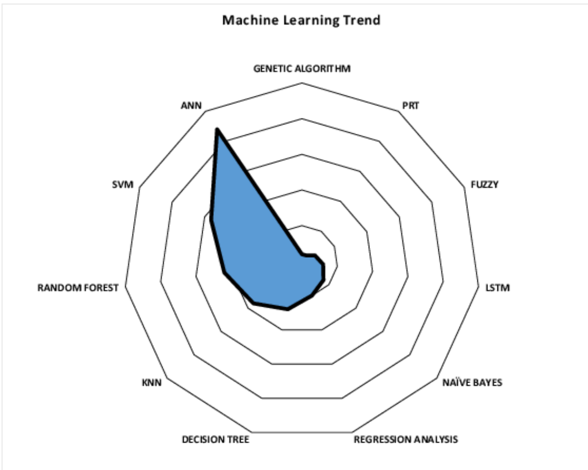

FIGURE 2. **Trend ML model for PdM [20].**

The application of ANN models in predictive maintenance offers distinct advantages over traditional methods, due to their advanced data processing capabilities and adaptability in complex industrial environments. ANN-driven evaluation methods, specifically models employing architectures such as CNN and LSTM, achieve exceptionally high prediction accuracy, with studies showing a 15% improvement over conventional methods, reaching a rate of 98.5% accuracy even under noisy conditions [21]. This robustness to data imperfections significantly enhances their real-world reliability. Additionally, ANN models demonstrate remarkable efficiency by achieving over 99% accuracy in classifying motor health, which, combined with their low computational complexity, makes them ideal for deployment on edge computing devices, facilitating on-site and real-time analysis [22]. Leveraging real-time sensor data, ANN models provide precise failure predictions, contributing to reduced machine downtime, cost savings, and improved worker safety by enabling proactive maintenance [23]. Furthermore, hybrid ANN configurations, like CNN-LSTM, enhance predictive accuracy and reduce model complexity, outperforming traditional architectures, such as standard LSTM and GBDT, with an F-Score increase from 93.34% to 97.48% [24].

One of the challenges in developing ML models for predictive maintenance is the limited faulty data that can represent the problems faced by machines [19], [25], [26]. Therefore, several studies have proposed synthetic data-generation methods that use various methods to mimic real data. For example, [27] used synthetic data to train predictive maintenance algorithms in high-reliability analog electronic systems to ensure their adaptability to upgrades. The method for creating synthetic data involves simulation-assisted failure analysis combined with generative adversarial networks (cGANs). In addition, [28] performed predictive maintenance on high-performance computing (HPC) systems, and the use of synthetic data for this research addressed data imbalance and label scarcity. Synthetic data can be created using data augmentation techniques such as oversampling and undersampling. Synthetic data provides more efficient access to data and enables better analytics by addressing privacy concerns and allowing analysts to work with realistic datasets without the need for additional consent or privacy measures [29], [30]. However, a balance between realistic and synthetic data characteristics must be obtained to ensure that the designed model is not biased toward the wrong side of the decision.

This study explored the use of ML algorithms and IoT sensors to develop a predictive maintenance model for CT scanning machines. Synthetic data were generated such that the ML model could detect anomalies in sensor readings, indicating the likelihood of a breakdown. The aim is to prevent unexpected failures and improve equipment performance, availability, and dependability. This approach can help healthcare organizations avoid costly downtimes and equipment failure during critical procedures. Studies have shown that PdM can reduce maintenance costs by up to 8% and production losses by up to 11% [31].

Implementing PdM in CT scans requires technical advancements, adherence to regulatory standards, and ethical considerations. Ensuring patient safety, data security, and compliance with healthcare regulations is critical for the successful deployment of PdM systems. By addressing these factors, healthcare providers can leverage the PdM to enhance the reliability and efficiency of critical medical equipment.

II. METHODOLOGY

The methodology encompasses several crucial stages, such as the setup of sensors, as described in [32], data preprocessing, and development of a machine learning (ML) framework. Each step was designed according to the scope of the study and selection of the study site.

A. DATA ACQUISITION

Based on literature review as cited on [32], six sensor parameters like current, radiation, temperature, humidity, acceleration on x and y was selected for PdM model.The radiation sensor is crucial because PdM is applied to CT scan machines, which emit radiation. It was selected because, according to a report from the radiologist, radiation tube always need to be maintained, even when the equipment is newly replaced. Current was selected as a parameter for predictive maintenance because it helps detect electrical anomalies, operational inefficiencies, and potential equipment failures in the CT scan machine. Acceleration sensor was used to check the vibration of CT scan machine, vibration is crucial parameters for PdM including including temperature and humidity [33]. The use of cables inside the CT scan room was minimized because it is an emergency area for patient handling and continuous movement is required.

All sensor data were transmitted to the IoT Gateway using wireless communication protocols, which is a 4G network. According to [34], wireless communication transmits information through the air using electromagnetic waves such as radio frequencies, infrared, and satellite signals, eliminating the need for cables. Maxis Telecommunication was chosen as the service provider because it shows the strongest signal during in-house signal measurement compared to Celcom, even though the CT scan room is located underground. The incoming data are processed in the IoT gateway to convert the data formats based on the sensor specifications. Each type of data sensor is transmitted at different time intervals, owing to the different sensor specifications. To secure reliable data transmission, a bridge gateway was used to transfer the preprocessed data to the network server. The advantage of a bridge gateway is that it increases flexibility, adaptability, and cost reduction by providing a uniform-use interface, detachable architecture for customization, and protocol translation for accurate data processing [35]. The network server forwards data to the MongoDB NoSQL database. MongoDB was used because of its capability to handle large unstructured data efficiency values. Researchers have found that each NoSQL database, including MongoDB, has unique optimization and characteristics that directly impact performance metrics such as data loading time and execution times for read and update operations [36]. Data from this database for the full year 2023 were utilized in this study to enhance model stability and test the machine learning prediction model.

B. DATA PREPROCESSING

Data preprocessing is a critical phase in any predictive maintenance program. It involves cleaning and preparing data to ensure accuracy, completeness, and in an appropriate format for analysis [37], [38]. The purpose of data preprocessing is to convert raw data into a form that can be readily analyzed using statistical or machine learning methods.

The selected data are plotted in their respective distributions to represent each feature. During the early development of the model in [32], the collected data for the development of the model only represent the normal condition of the machine because the machine is working well and patient scanning is performed as usual. Additionally, every reading is collected at different intervals of time due to the sensor's capability. Each reading is recorded in its respective unit, for example, temperature in degrees Celsius. To develop an ML model that can predict breakdown, abnormal synthetic data were generated from real normal data by expanding the head and tail of the data distribution, as shown in Figure 3. To ensure that abnormal synthetic data are realistic and useful, they must be generated within the sensor-detection range. This involves understanding the limits and characteristics of the sensors used in data collection to mimic real-world examples [39]. Real and synthetic data were combined into a single file, and the total number of data points was 56458. These data were labeled into two classes: low for normal data (indicated by 0) and high for abnormal data (indicated by 1). The conditions for labeling the data were based on literature review, machine specifications, and sensor readings. All the labeled data were fed into the ANN model to execute the training and testing processes. The developed model was tested and integrated into a live dashboard for real-time testing.

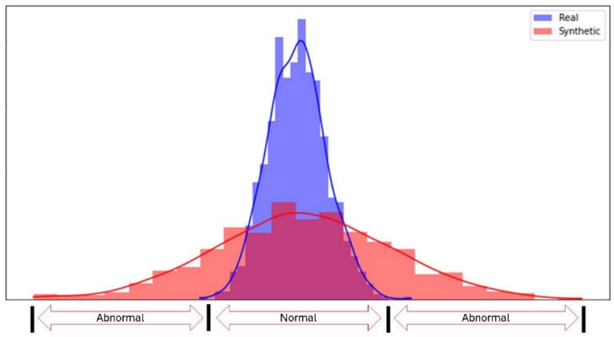

FIGURE 3. Distribution of real and synthetic data.

The previous dataset used in [32] comprises 5000 synthetic data points, which are considered small. A synthetic data generation method was employed to generate new data and force the dataset to be distributed normally using the mean and standard deviation values. Consequently, the data were expanded based on a normal distribution rather than the original distribution. The aim of this stage is to maintain the original distribution, making the synthetic data more realistic and providing a better representation of the real scenarios. By utilizing a more extensive dataset, spanning from January 2023 to December 2023, more accurate results can be obtained. Equation 1 demonstrates the normalization process of the data, which was then further normalized using min-max scaling. After this step, noise was added to the normalized data using Equation 2. The noise was calculated using Equation 3, where the noise factor was determined until it reached the maximum value within the range of the sensor. The tools used for synthetic data generation are listed in Table 1.

$$\text{normalized\_value} = \frac{\text{value} - \text{min}}{\text{max} - \text{min}} \tag{1}$$

$$\text{noisy\_value} = \text{normalized\_value} + \text{noise} \tag{2}$$

$$\text{noise} \sim \mathcal{N}(0, \sigma \cdot \text{noise\_factor}) \tag{3}$$

Imbalanced datasets can hinder the ability of ML models to accurately learn patterns from minority classes, thereby impacting their predictive performance and leading to skewed outcomes [40]. By generating synthetic data, the development

TABLE 1. Tools to create synthetic data using head and tail expansion.

Software/Compiler/Library	Version
Jupyter Notebook	3.0.12
Numpy	1.21.6
Pandas	1.3.5
Matplotlib	3.5.2

of an ML model will produce better results because ML is highly dependent on the amount of training data. Synthetic data for abnormal conditions are highly desirable because all the collected data are from normal machine conditions. The balance data is important to ensure the ML model is not bias into one class only that will produce low accuracy results [41], [42], this synthetic data generation method is very helpful for PdM model development.

C. MACHINE LEARNING FRAMEWORK DEVELOPMENT

Developing an Artificial Intelligence (AI) model is a crucial step in predictive maintenance, because it entails creating a model capable of accurately forecasting equipment failures before they occur. This section outlines the creation of an ANN framework that utilizes IoT data as the input and machine breakdown risk as the output. Figure 4 shows the development of the ANN framework, and the completed ANN framework was presented in [32]. The development process of machine learning begins with manual collection of data from the dashboard, as all sensor readings are uploaded online. Subsequently, data preprocessing was performed to sort the data, and abnormal synthetic data were generated to balance the datasets. Based on the original and synthetic data, ML was trained and tested until acceptable prediction accuracy was obtained. Once the model is stable and can be predicted accurately, it is integrated into the dashboard using the Flask API and the output is displayed.

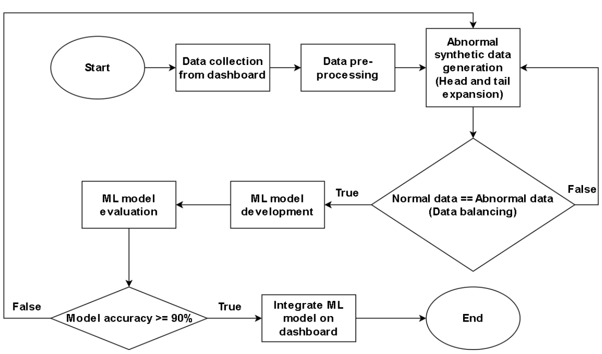

FIGURE 4. Flowchart for ANN development using IoT sensors data.

The ANN framework received six input fetaures, produced two outputs (low and high risk of breakdown), and consisted of two hidden layers. Figure 5 show ANN architecture where 6 dimensions of the input data produced binary output, each row from this 6 dimensions of data represent the time line data was collected. All of this data was normalized before insert into ML model. In total, 56456 data points were randomly split into 70% training and 30% testing using the `model_selection.train_test_split` function available in the Scikit-learn library. This ratio of data splitting was selected because according to [43] and [44], this ratio of data split is the best to feed into the ML model. The framework is written using the Python language, TensorFlow library, and all tools used, as stated in [32].

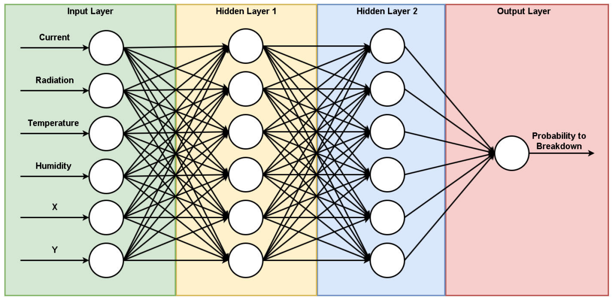

FIGURE 5. Flowchart for ANN development using IoT sensors data.

The ANN model in this architecture is structured for binary classification, featuring two hidden layers with six neurons each and ReLU activation to capture complex patterns, and a single-output neuron with a sigmoid activation for probability-based classification. The model is compiled using the Adam optimizer for efficient weight adjustment, with binary cross-entropy as the loss function, suitable for binary outcomes. Training is set for 100 epochs with a batch size of 32, allowing gradual model optimization. To improve convergence, the input features are scaled between 0 and 1 using MinMaxScaler. The model's accuracy is tracked as a performance metric, while PlotLossesCallback provides real-time visual feedback on accuracy and loss, supporting effective model monitoring and fine-tuning during training.

The Sobol method was used to perform a sensitivity analysis on the selected features, evaluating their individual and interactive effects on the model's predictions. The performance of the model was measured based on the classification results and is represented as the percentage of correctly classified data. A confusion matrix was used to analyze the assignment of data across all categories. For the binary classification model, the confusion matrix was visualized as a 2×2 matrix. There are four key variables in the confusion matrix: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The performance of the ML model was evaluated using this method.

III. RESULTS

In predictive maintenance, IoT sensor data are analyzed to detect trends and patterns that may signal upcoming machine failures. This analysis evaluates the characteristics of the data, such as the minimum, maximum, and average sensor readings. By identifying the normal value range for each sensor and spotting any anomalies, the maintenance teams can compare the current sensor readings with these benchmarks. Any deviation from the norm can help predict a potential equipment failure.

Figure 6 to 11 show the distribution of features for 2023 fed into the machine learning (ML) models. The current value is mostly around 2 to 7A (normal state), and during scanning, it can reach up to 80A. The radiation value is collected cumulatively owing to sensor limitations as it accumulates radiation data for 3 minutes before it can produce the output. This causes the radiation sensor readings to be very large, spiking to 2 million uSv/h when the technician performs weekly calibration of the CT scan machine. This scenario does not occur when a patient is present, as it is observed that the radiation detected is up to 600000 uSv/h during patient scanning. Temperature and humidity readings were obtained from a sensor unit located inside the CT scan room to monitor the environment for the machine to operate at optimal performance. The last sensor was an accelerometer used for the vibration measurement. It is placed near the rotational force of the machine because the vibration increases if any abnormality is detected in relation to the mechanical parts. The values of vibration vary owing to the vibration produced during scanning and return to the initial position after scanning is completed. All of these sensors are non-invasive because the CT scan machine is under radiology care and is still under leasing services by the manufacturer. The analysis of data distribution is important to ensure that the range of data is consistent throughout the year and to identify abnormalities in the sensor readings. Table 2 lists the number of data points and their features for each month. There are sets of data that are less than the average value owing to system maintenance, server downtime, and patient emergency, which causes the sensors that were positioned at the gantry area to be removed (radiation and acceleration sensors).

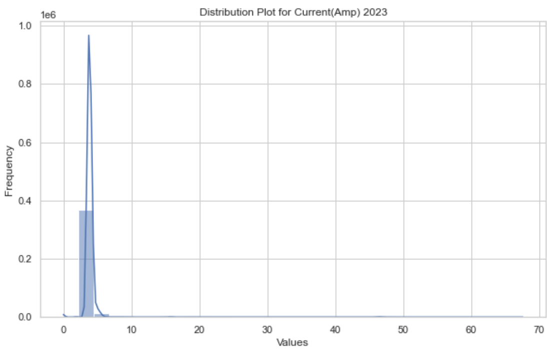

FIGURE 6. Distribution of current value (Amp) vs frequency for year 2023.

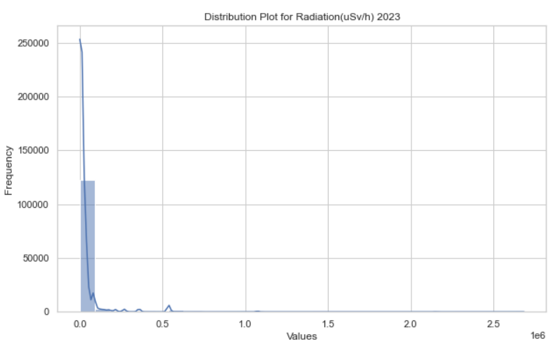

FIGURE 7. Distribution of radiation value (uSv/h) vs frequency of year 2023.

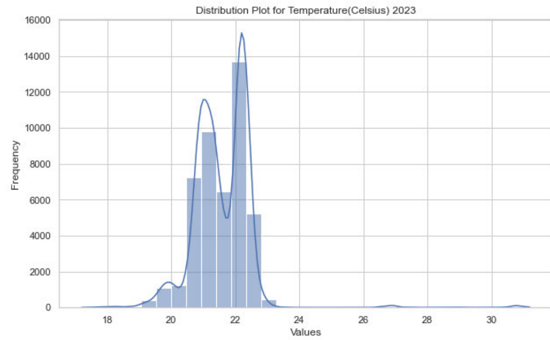

FIGURE 8. Distribution of temperature value (Â°C) vs frequency for year 2023.

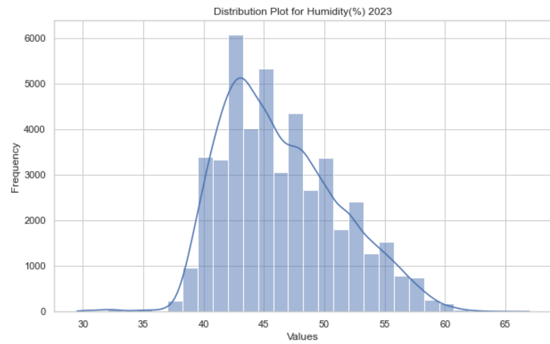

FIGURE 9. Distribution of humidity value (%) vs frequency for year 2023.

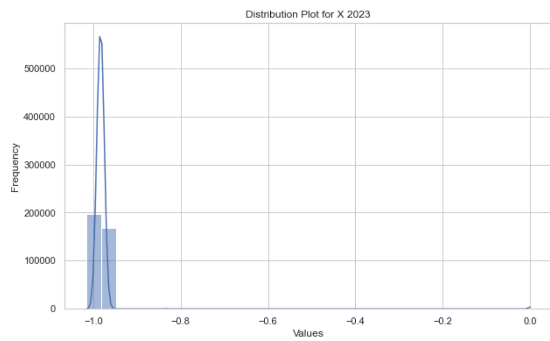

FIGURE 10. Distribution of accelerometer on X-axis vs frequency for year 2023.

By comparing the IoT sensor data with the patient scan log, it is possible to identify any correlations between specific sensor readings and the conditions of the machine or the patients being scanned. Based on this reading validation, changes in the values of five out of six features can represent the scanning operation of the CT scan machine: current, radiation, temperature, humidity, and acceleration at the Y-axis value. Overall, the data analysis performed on the

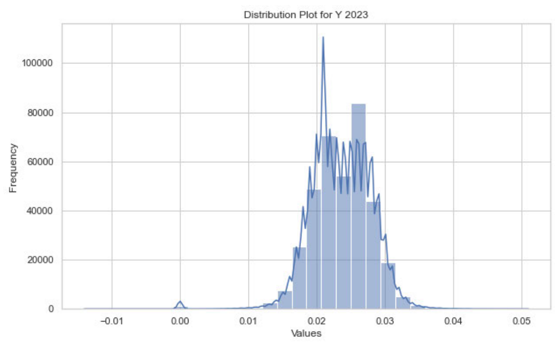

FIGURE 11. Distribution of accelerometer on Y-axis vs frequency for year 2023.

TABLE 2. The number of iot data points collected for all features in 2023.

Month	Current	Radiation	Temperature and Humidity	Acceleration at X and Y axis
January	25841	8604	3089	25839
February	24445	8143	2923	24444
March	36943	9994	4407	10000
April	35118	11791	4492	10000
May	36607	12194	4419	36595
June	35920	11972	3275	35913
July	22197	8067	2869	22206
August	31100	11693	3793	31100
September	32604	10856	3788	32601
October	34537	12001	4297	34519
November	34514	11953	4055	34525
December	34523	11867	4427	35663

IoT sensor readings provided valuable insights into the performance of the CT scan machine and potential issues with the equipment.

The evaluation results reveal that after normalizing the data using the min-max scaler method and incorporating breakdown risk, the trained model exhibits a remarkable capability to distinguish between normal and abnormal conditions in the context of the IoT-connected CT scan machine. Notably, the results presented in Table 3 demonstrate an average accuracy of 97.58% across ten iterations during the training stage, affirming that all features collectively contribute to the predictive accuracy of the model. This accuracy is higher than that presented in [32] which is 95.91%. Additionally, the results show an average binary cross-entropy loss of 7.01% across the ten iterations, indicating that the model's predictions closely align with the actual values. The low binary cross-entropy loss value reinforces the model's ability to minimize errors effectively during training, suggesting that all features contribute not only to high accuracy but also to reducing prediction error.

Overall, the data analysis performed on the IoT sensor readings provided valuable insights into the performance of the CT scan machine and potential issues with the equipment. To address the need for parameter sensitivity analysis, a Sobol method assessment was conducted to evaluate the influence of each input parameter—current, radiation, temperature, humidity, x, and y on the model's predictions. The analysis revealed that radiation is the most

TABLE 3. The ANN performance in 10 iterations of training and testing.

Iteration No	Accuracy	Loss
1	0.9748	0.0729
2	0.9547	0.1191
3	0.9482	0.1410
4	0.9887	0.0364
5	0.9948	0.0171
6	0.9486	0.1370
7	0.9906	0.0344
8	0.9874	0.0539
9	0.9846	0.0472
10	0.9859	0.0420
AVERAGE	**0.9758**	**0.0701**

significant parameter, with a first-order sensitivity index of 0.548, indicating its substantial individual impact on the model output. Additionally, it demonstrated a high total sensitivity index of 0.914, which includes interaction effects, confirming its dominant role in influencing the model. A notable interaction was observed between radiation and humidity, with a second-order sensitivity index of 0.366, while the remaining parameters (current, temperature, x, and y) showed minimal individual and interaction effects. These findings underscore that the model is primarily influenced by radiation, aligning with expectations based on domain knowledge, and validate the robustness and interpretability of the modeling approach.

In addition, the confusion matrix depicted in Figure 12 provides visual evidence of the proficiency of the ANN framework in achieving precise output predictions, as evidenced by its consistently low error rate. Specifically, the high class, which represents a high risk of breakdown, contains 8410 total data points and has a precision of 0.9912. The low class, which represents a low risk of breakdown, contains 8527 total data points and has a precision value of 0.9994, indicating nearly perfect classification accuracy. However, it is important to note that these results are a combination of real and synthetic data, and may not include outliers or other types of data that can occur in real-world situations.

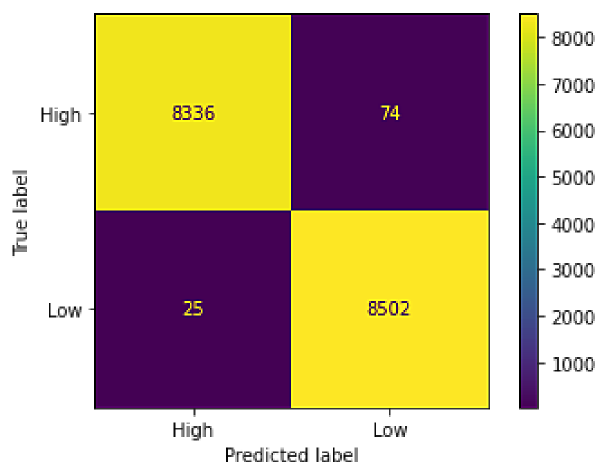

FIGURE 12. Confusion matrix of ANN based breakdown predictions.

When bad data is collected, it typically impacts evaluation modeling by introducing noise, outliers, or inaccuracies that can skew predictions, reduce model accuracy, and undermine the reliability of the results. However, in this case, the impact of bad data is minimized due to the use of synthetic data generation that has expanded within the range of the sensor specifications. This approach ensures that all data, including potentially faulty data, remains within the valid sensor range, as the synthetic data aligns with the sensors' capability to capture only within their defined specification limits. By generating synthetic data that covers the sensor's entire operational range, consistency and robustness in the evaluation modeling will be maintained, effectively neutralizing the adverse effects of bad data.

A sample of the dashboard display is shown in Figure 13, which shows the sensor monitoring and prediction results on the right (smart meter with color labels: green, yellow, and red). Green indicates a low risk of breakdown, whereas red indicates a high risk. The calculated value of the risk percentage relies on the measured readings from each sensor with the same priority level on an hourly basis.

The proposed model in [32] has shown its accuracy when the prediction of the breakdown results from October 2023 to December 2023 is consistent with the condition of the machine (as shown in Figure 14 to 16). This study enhances the model presented in [32], which used data only from September 2022 to January 2023. The improved version now incorporates a complete dataset collected from January to December 2023. Figure 13 represents the normal working conditions of the CT scan machine, which shows that the predictions vary from low to high because rapid changes in the scanning and non-scanning operations produce variations in the predicted values. In contrast to the October 2023 incidents (Figure 14), the data from November 2023 (shown in Figure 15) indicate that most of the predicted breakdown risks are constantly high (reading 1.0). The engineer in charge confirmed that the machine had technical issues, which led to the reading shown in Figure 16. Repair work was performed in December 2023 because the technician detected the problem in early December 2023.

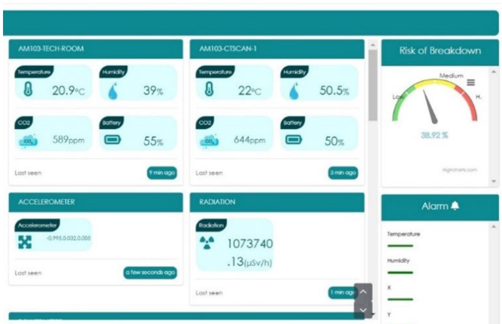

FIGURE 13. **Dashboard displays the breakdown prediction result (top right).**

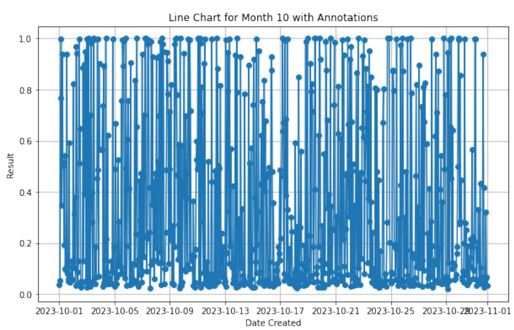

FIGURE 14. **Risk of breakdown prediction results in October 2023 (0 is low, 1 is high).**

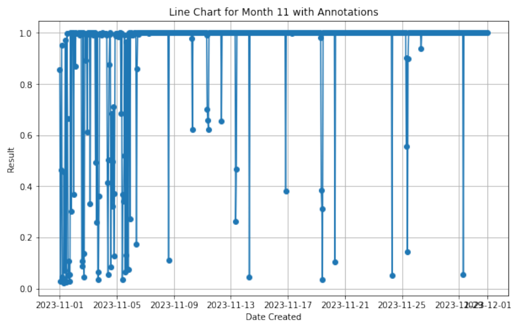

FIGURE 15. **Risk of breakdown prediction results in November 2023 (0 is low, 1 is high).**

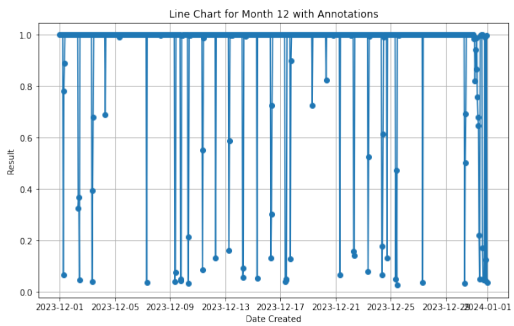

FIGURE 16. **Risk of breakdown prediction results in December 2023 (0 is low, 1 is high).**

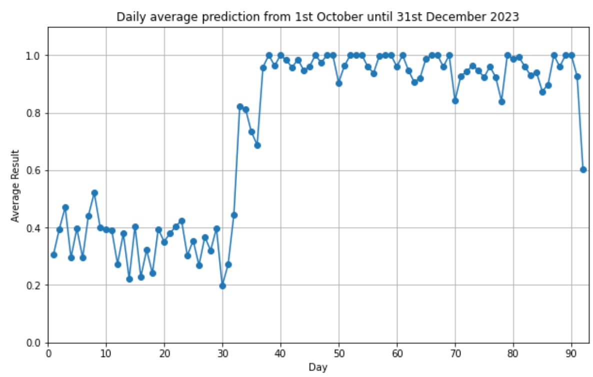

FIGURE 17. **Average risk of breakdown prediction results in daily basis from 1st October until 31st December 2023.**

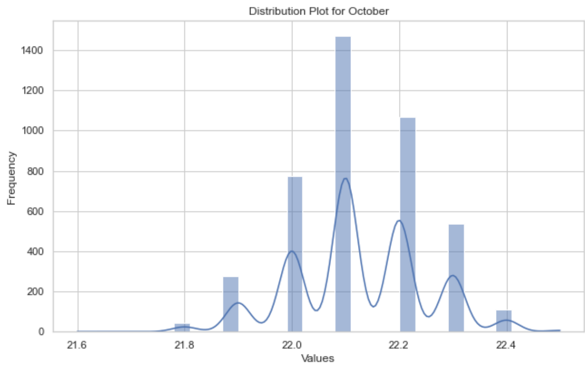

FIGURE 18. Distribution of temperature reading in October 2023.

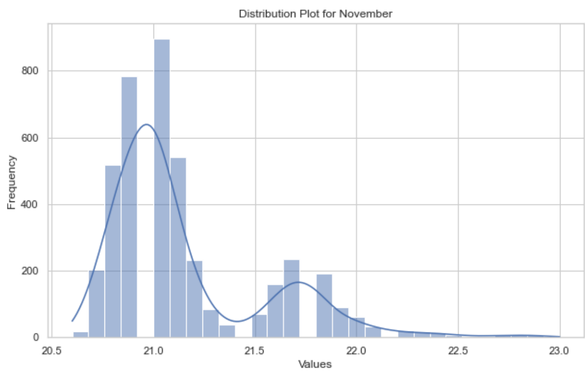

FIGURE 19. Distribution of temperature reading in November 2023.

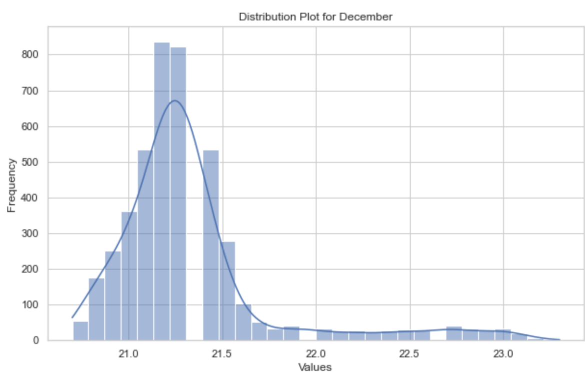

FIGURE 20. Distribution of temperature reading in December 2023.

Figure 17 shows the overall prediction of the breakdown risk for the three months by calculating the daily average values. Based on further analysis of the collected data, the reading that leads to a high risk of breakdown is temperature values where the machine is working below its optimal working condition (22°C up to 26°C), as stated in [45]. As shown in Figure 18, the normal temperature readings during October are documented and ranged from 21.6 degree Celsius to 22.5 degree Celsius. The readings in November and December (Figure 19 and 20, respectively) show readings below the optimal working condition of the machine, with a peak at approximately 21°C.

IV. CONCLUSION

In conclusion, the implementation of an Artificial Neural Network (ANN) model for predictive maintenance on IoT-connected CT-scan machines has demonstrated significant efficacy in predicting potential failures. The model was trained using synthetic data generated by expanding the head and tail of the real data, and it considered six different features, including temperature, humidity, radiation, current, and acceleration along both the X and Y-axes. The output of the ANN model provided a binary risk assessment, indicating either a high or a low risk of breakdown. Achieving a remarkable accuracy of 97.58%, the model has proven to be a dependable tool for predicting the maintenance requirements for CT scan machines, thereby enhancing their operational reliability and reducing unexpected downtimes. This method has been proven to detect machine breakdowns because the results show a high risk in November 2023, and the repair work was performed in December. These results were obtained based on the model in [32] but retrained with an extensive number of data points. By identifying potential breakdowns before they occur, healthcare providers can minimize downtime and extend the lifespan of equipment, leading to more efficient and effective patient care. Overall, the use of ANN models for the predictive maintenance of medical equipment, such as CT scan machines, has significant potential to enhance the quality of healthcare and reduce the costs associated with equipment failures. In the future, the prediction model will be evaluated in other sites and hospital settings.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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