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IoT FOR PREDICTIVE MAINTENANCE OF CRITICAL MEDICAL EQUIPMENT IN A HOSPITAL STRUCTURE

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Abstract. *Predictive maintenance (PdM) allows the prediction of early failures of medical equipment before they occur. It helps to diagnose the defaults of critical equipment in a hospital structure, namely MRI. Founded on the analysis of data collected in real time of the right parameters, thanks to intelligent sensors positioned on the equipment, using Internet of Things (IoT) technology and the practice of machine learning tools. The objective of this techniques is the implementation of algorithms capable to predict an anomaly, which will make equipment and maintenance tools increasingly autonomous and intelligent. Therefore, the idea of this project is to develop a wireless sensor network to ensure continuous monitoring of the state of MRI. The implemented solution includes an IoT monitoring system of the cold head's cooling circuit. Based on the vibrations at the pump, it allows to monitor the motor circuit, inform the staff at each abnormal state of this system, and protect this device against any future anomalies. Thanks to the CNN algorithm implemented in this solution, the results are very satisfactory, with an accuracy >98%. This solution can be integrated into a general predictive maintenance solution for the most sensitive equipment in a hospital.*

Keywords: critical medical equipment, predictive maintenance (PdM), internet of things (IoT), magnetic resonance imaging (MRI)

IoT DO PREDYKCYJNEJ KONSERWACJI KRYTYCZNEGO SPRZĘTU MEDYCZNEGO W STRUKTURZE SZPITALA

Streszczenie. *Konserwacja predykcyjna (PdM) umożliwia przewidywanie wczesnych awarii sprzętu medycznego przed ich wystąpieniem. Pomaga zdiagnozować usterki krytycznego sprzętu w strukturze szpitala, na przykład MRI. Opiera się na analizie danych zbieranych w czasie rzeczywistym odpowiednich parametrów, dzięki inteligentnym czujnikom umieszczonym na sprzęcie, przy użyciu technologii Internetu rzeczy (IoT) i narzędzi uczenia maszynowego. Celem tych technik jest wdrożenie algorytmów zdolnych do przewidywania anomalii, które sprawią, że sprzęt i narzędzia konserwacyjne będą coraz bardziej autonomiczne i inteligentne. Dlatego ideą tego projektu jest opracowanie bezprzewodowej sieci czujników w celu zapewnienia ciągłego monitorowania stanu MRI. Wdrożone rozwiązanie obejmuje system monitorowania IoT obwodu chłodzenia zimnej głowicy. W oparciu o wibracje pompy pozwala on monitorować obwód silnika, informować personel o każdym nieprawidłowym stanie tego systemu i chronić to urządzenie przed wszelkimi przyszłymi anomaliami. Dzięki algorytmowi CNN zaimplementowanemu w tym rozwiązaniu, wyniki są bardzo zadowalające, z dokładnością >98%. Rozwiązanie to można zintegrować z ogólnym rozwiązaniem konserwacji predykcyjnej dla najbardziej wrażliwego sprzętu w szpitalu.*

Słowa kluczowe: krytyczny sprzęt medyczny, konserwacja predykcyjna (PdM), internet rzeczy (IoT), rezonans magnetyczny (MRI)

Introduction

Today, medical equipment has become more and more sophisticated and complex, it has revolutionized thanks to technological advances. With this development of medical equipment, hospitals must guarantee that their critical medical devices are safe, accurate, reliable and operative, as well as ensuring high-quality patient care at a rapid pace, while adopting optimal maintenance strategies that improve equipment performance to reduce maintenance charges, effort and operations. Aiming to decrease unexpected equipment interruption and increase their reliability, new technologies make it possible to change maintenance strategies from curative maintenance to predictive maintenance [19].

Critical medical devices that are subject to dynamic development in order to develop effective diagnostic methods, to identify the symptoms of diseases and possible treatments, and to anticipate possible complications to patients in a hospital structure, they must maintain a normal operation to ensure all these functions, and anticipate any defect that could reduce partially or totally its effectiveness. Among this critical equipment is the MRI, which is one of the most important devices in each hospital structure [18]. MRI manufacturers typically provide chiller temperature and helium level monitoring to track the status of this system [1], but these tools require regular monitoring and verification of their value by the technical staff, which leaves a large margin of error.

Temperature or helium level measurements give good results for long-term monitoring, but their effectiveness in predictive maintenance is not always justified. Moreover, the measured parameters are not accessible to the maintenance service and cannot be evaluated by an online monitoring system.

Decrease in helium level due to its loss because of a leak, failure of the cryogenic circuit or the chilled water system or failure of the cold head pump are the main causes of failures related to the cryogenic cooling system. All these faults can be predicted by a monitoring system and the maintenance of the system can be managed in the best conditions. This surveillance system matches the pressure and temperature setup established by the fabricator.

To ensure the performance of this critical medical equipment, predictive maintenance based IoT allows more effective use of current assets by providing the capacity to predict any defect before it occurs [19], through smart sensors positioned on the equipment, it continues to intervene in a timely and accurate manner, avoiding sudden shutdowns that require multiple interventions in an undetermined amount of time, while ensuring to improve performance and reduce maintenance costs of that equipment [19].

We propose a solution for cold head monitoring in MRI, independent of the solutions provided by the MRI system manufacturers. So, the goal of this project is to create a wireless sensor network, to ensure continuous monitoring of the state of MRI including the cooling circuit (cold head), by detecting vibrations at the pump and motor circuit, inform the staff at each abnormal state of this system, and protect this equipment against any future anomalies.

The first part of our project focuses on IoT, where we have designed an electronic instrument using a Raspberry Pi and an ADXL345 sensor to measure and record vibrations from MRI pumps. This data is then processed and analyzed to detect early signs of failure. Additionally, we have implemented a secure data transmission system using the Advanced Encryption Standard (AES) protocol, ensuring the confidentiality and integrity of sensitive information.

The second part of our project concentrates on AI, where we leverage a database from the Bearing Data Center to train deep learning models. We employ methodologies like convolutional Neural Networks (CNN) and Artificial Neural Networks (ANN) for data classification and potential detection of defects in MRI pumps. The performance of these classifiers is evaluated using specific measures, such as accuracy, and visualized using a confusion matrix and scatter plots to demonstrate the effectiveness of our model.

In this article, we provide a detailed description of the methodology used, including the dataset from the Bearing Data Center, data preprocessing steps, proposed deep learning classification models, performance measures used, and validation methods. We also discuss the obtained results, highlighting the advantages of our approach and the prospects for improving predictive maintenance of MRI systems.

The remaining portion of the paper is planned as follow. In the following section we will outline the current state of the art of predictive maintenance and IOT with the appropriate techniques used in our project, a technical study of MRI is described in Sect. 2, in Sect. 3 there are methods and materials used in our project, then the results and discussions of solutions based on an experiment are represented in Sect. 4. The conclusion of this paper is presented in Sect. 5.

1. IoT-based PdM

The use of an IoT-based PdM system, where sensors are used to collect data, will obtain the status of equipment and provide warnings that will activate the preparation of a maintenance action before attainment a failure. It involves sensors to capture continuous real information of key reasons that result in deficiencies, including vibration, temperature, noise levels, pressure, energy consumption, etc.

Effective implementation of predictive maintenance through IoT hinges on advanced data analysis techniques and machine learning algorithms [12]. These tools leverage historical performance data to identify significant patterns in equipment performance, detect deviations as anomalies, uncover precursor signals indicating potential future failures, and subsequently:

- predict the likely time of asset failure,
- identify the specific component of the equipment responsible for the failure,
- recommend optimal timing for preventive actions.

Enforcing the Predictive Maintenance (PdM) policy will enhance equipment accessibility by enabling the early detection of potential failures and minimizing the costs associated with maintaining excess parts inventory. Moreover, the adoption of such a strategy will positively impact equipment lifespan and quality, leading to heightened levels of safety and a reduction in both downtime and emergencies that pose threats to people's lives [19].

1.1. Predictive maintenance-based vibration analysis

The technological innovations in the field of maintenance of technical medical equipment, has led many constructors to abandon traditional periodic maintenance strategies and change them with predictive maintenance policies. This later has been implemented in various manufacturing and service industries to ensure safety, reliability, efficiency, availability, quality and environmental protection [16].

Predictive maintenance plans target specific maintenance activities as soon as the equipment is required, as opposed to standard maintenance plans, which are focused on consistently maintaining all machines and acting fast in the event of an unexpected failure.

Predicting a failure on equipment is a major concern of biomedical maintenance managers to define the most relevant strategies from a technical and economic point of view. More than that implementing a predictive maintenance strategy allows significant savings to be made compared to curative or preventive maintenance, because the tasks are only carried out at the appropriate time. As a result, we can diminish machine interruption and rise machine life and general productivity as reflected in figure 1.

So, predictive maintenance is able to be summarized as a maintenance methodology that enables machines to be serviced before they fail, thus reducing unplanned downtime and providing a more reliable planning tool for typical preventive maintenance work [20]. In our case we will use predictive maintenance as a working tool; which will allow us to predict and detect failures of the MRI system before they happen.

A comprehensive predictive maintenance program should incorporate a variety of monitoring and diagnostic techniques. These include thermography, vibration monitoring, tribology, process parameters, visual inspection, ultrasonic testing, and other non-destructive testing techniques [16].

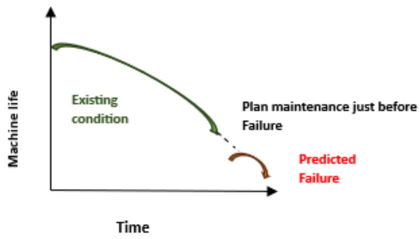

Fig. 1. Minimize machine downtime and increase machine life

Vibration is characterized as a recurring or periodic signal that repeats at a specific interval. Machines with rotating or moving parts produce a vibration profile, allowing the application of vibration-based analysis methods for predictive maintenance. Vibration analysis serves as a key technique among various predictive maintenance methods for observing and assessing critical machinery, equipment, and systems within a plant [19].

As previously mentioned, vibration analysis is primarily employed in maintenance management programs to monitor rotating equipment, detect potential issues at an early stage, and prevent catastrophic failures. Specific faulty equipment exhibits abnormal and intricate yet identifiable vibrations. Over time, monitoring the normal vibration profile of equipment allows for the establishment of baseline data. Any unexpected deviations, such as changes in load, can cause alterations in frequency and amplitude. These changes can be isolated and compared to vibration profiles associated with common failure modes [19].

Vibration analysis can also be applied to assess fluid flow in pipes or vessels, identify variations in vibration levels in critical components like pumps and compressors, detect leaks, and perform various non-destructive testing functions to enhance the reliability and performance of crucial plant systems. This technique will be utilized in our project to detect potential failures in the compressor's pump.

In this study, we will utilize a different database consisting of vibrations from drive end accelerometer data. The vibration signals from this system exhibit similarity to those of the MRI pumps, allowing us to apply the same analysis approach [9, 11, 21].

1.2. Internet of things (IoT)

The Internet of Things (IoT) relates to a network of interlinked computing equipment, mechanical and digital machinery, objects, or even individuals. These entities can communicate and transmit data over a network autonomously, without requiring direct human-to-human or human-to-machine interaction, enabling intelligent perception [2]. As per the definition by the Institution of Electrical and Electronic Engineers (IEEE), IoT is described as "a network of objects, each equipped with sensors, that are connected to the Internet" [6].

Within an IoT ecosystem, there are web-connected intelligent devices equipped with embedded systems, encompassing processors, sensors, and communication hardware. These devices are designed to gather, transmit, and process data from their environment. They transmit the gathered sensor data by linking to an IoT gateway or another control device, which subsequently transfers the data to the cloud for analysis. The choice of connectivity, networking, and communication protocols utilized by these web-enabled devices is typically tailored to the specific IoT applications being employed. Furthermore, IoT can harness artificial intelligence (AI) and machine learning techniques to optimize and augment the data collection processes.

Below in figure 2 we present our schematic illustration of the proposed vibration monitoring IoT system.

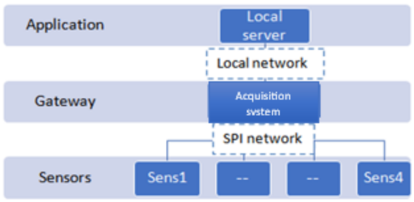

Fig. 2. Schematic diagram of the proposed vibration monitoring IoT system

The healthcare industry is increasingly embracing the Internet of Things (IoT) to enhance overall quality and patient satisfaction. Hospitals, in particular, are investing significant efforts in implementing IoT technology, enabling doctors to monitor patients through sensing and wireless technologies [5, 17]. The introduction of IoT is anticipated to lead to an 83% growth in Predictive Maintenance (PdM) practices within industrial companies over the next two years [2]. Furthermore, PdM is expected to bring about a 12% reduction in costs, a 9% increase in uptime, a 14% decrease in health, environmental, and quality risks, and a 20% extension in the lifespan of assets [15].

In the healthcare manufacturing sector, establishing a predictive maintenance (PdM) program comprises three core steps: data collection, data analysis, and decision-making. Various PdM techniques, like vibration analysis, oil analysis, and thermography, can be employed to assess equipment conditions [3]. For instance, vibration analysis is a commonly used method to evaluate moving parts of electromechanical systems, predicting potential failures like motor breakdowns, belt or chain slippage, and wear and tear on gears and sprockets.

2. Technical description of MRI

In this section, the design of MRI equipment is assessed, and the elements of a contemporary MRI system are dissected. A mechanism for sending and receiving electromagnetic radiation pulses in the RF band is necessary, as is a strong, homogeneous magnetic field. Additionally, spatial encoding necessitates complex static field manipulation in three orthogonal dimensions [8].

The essential components required for all Magnetic Resonance Imaging Systems (MRIS) include the following elements [10]:

- A powerful magnet capable of generating a magnetic field within a spherical volume of 40–50 cm.
- A series of wedges engineered to enhance the uniformity of the magnetic field.
- A system for generating gradients tasked with creating linear gradients in the field intensity across all directions.
- An RF (Radio Frequency) transmission system utilized for generating and transmitting electromagnetic radiation pulses.
- A collection of RF receiver coils employed for detecting signals emitted by the patient.
- A computer system with the capability to receive input parameters and present images on a display.
- A computer subsystem proficient in controlling the application of RF pulses and gradients, organizing acquired data into images, and storing them.

2.1. Cryostat

The Greek words for "cold" and "steady", cryostat is formed from these words. You can utilize the cryostat, which is a little bigger version of the thermal vacuum flask, to keep your items cold. Helium cryogenic liquid, with a boiling point of 4.2 K (-268.9°C), is found inside the cryostat. The cryostat's main job is to stop heat from moving from nearby system parts, especially the gradient coils, to the cryogen. The pace at which liquid helium evaporates into the environment is slowed down by this thermal isolation [10].

2.2. Cryogens – liquid helium

Due to its incredibly low temperature, liquid helium is the preferred cryogen for super-conducting magnets. Outside of a plasma laboratory, it is quite challenging to obtain a temperature below 4 K. Because it makes up a (small) portion of the natural gas in some regions, helium is easily accessible. It is crucial not to waste it though, as it is a finite and declining resource. In numerous nations, notably the United States of America (USA) and Qatar, where there are significant subterranean fossil fuel deposits, massive extraction plants are currently in operation. Current research is looking towards superconducting magnets that can work at advanced temperatures due to the probable decline in the availability of helium and the inherent dangers of quenching (20 K). They use mixtures for example yttrium, barium and copper oxide instead of niobium/titanium [10].

2.3. Sources of vibrations in a MRI

The primary components of a MRI and their associated vibrations are as follows:

- The main magnet, responsible for creating a stable static magnetic field, is maintained at near absolute zero temperatures by the cold head. Vibrations associated with this component are typically caused by the cold head pump and are characterized by very low frequencies, around 1 Hz.
- The three gradient coils, used for spatial encoding, induce variations in magnetic field intensity, enabling the selection of different imaging planes and determining their thickness. Vibrations resulting from switching in these coils occur at pulsed frequencies of approximately 100 kHz.
- The radio frequency (RF) coils generate RF waves to excite hydrogen atoms in the body and capture the signals emitted during relaxation. Depending on the MRI scanner, vibrations from these coils can range from 64 MHz at a field strength of 1.5 T to over 299 MHz.
- The water compressor pump, located in the technical room, also contributes to vibrations, typically at frequencies of a few tens of hertz.

3. Methods and materials

This part is dedicated to present the different parts of the project. A hardware part of components that fit in the solution of our wireless sensor net- work and its descriptions. The same thing for the software part we will present all the simulation and configuration software with which we will try to make a simulation answering the problematic. The schema of the realized system described in the figure 3.

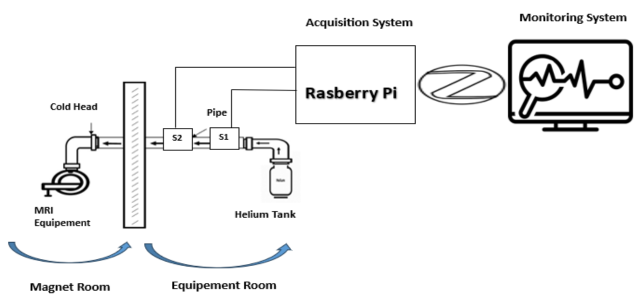

Fig. 3. Global schematic of the detection system

3.1. Electronic system

To execute our project utilizing ADXL345 and Raspberry Pi for pump vibration data acquisition, storage, and transfer, we followed a methodology that encompassed a needs analysis, hardware and technology selection, Raspberry Pi configuration, software development, and hardware and software integration. We conducted a thorough analysis of project requirements to define objectives and guide decision- making. ADXL345 was chosen as the vibration sensor [14], Raspberry Pi as the processing and storage platform, and necessary components were selected [7]. Raspberry Pi was configured with the appropriate operating system, communication settings, and security measures. Custom software was developed to acquire vibration data, manage storage, enable data transfer, and provide a user- friendly interface. Hardware and software were integrated, ensuring proper functioning and compatibility, and operational tests were conducted at each step.

Once the signals have been acquired, they are processed and transmitted to the monitoring system. This transmission is based on the AES encryption system.

The methodology for developing a program based on the ISO 10816 standard for measuring vibration data from MRI pumps involves defining the program objectives, selecting relevant measurement locations, collecting data using appropriate instruments, analyzing the data using suitable methods, interpreting the results based on the standard's criteria, generating clear reports with findings and recommendations, and conducting regular monitoring to assess their effectiveness. Adaptations may be necessary based on the specificities of the MRI and pump equipment, and reference should be made to the ISO 10816 standard for detailed guidance on measurement and evaluation procedures in the context of MRI pumps

To test the AI application of our system, we used scientifically approved data from CWRL.

Database overview

To successfully conduct our study on predictive maintenance of MRI pumps, we used a dataset obtained from the Bearing Data Center. This dataset is widely used in the field of fault detection in mechanical systems and provides vibration recordings from faulty bearings.

The dataset we selected is specifically related to drive-end bearing faults and consists of a total of 48,000 vibration records.

Data distribution

The "48k Drive End Bearing Fault Data" database consists of various attributes that describe the vibration recordings from faulty drive-end bearings (table 1).

Table 1. Data distribution

Attribute No	Signification	Values	Attribute
1	Defect Diameter	0.007", 0.014", 0.021"	Numerical
2	Motor Load (HP)	0	Numerical
3	Motor Speed (rpm)	1797, 1772, 1750, 1730	Numerical
4	Inner race	IR007_0, IR014_0, IR021_0	Text
5	Balle	B007_0, B014_0, B021_0,	Text
6	Outer race Position relative to Load Zone Centered	Centered, Orthogonal @3 :00, Facing @12 :00	Text

3.2. Classification approaches

ANN classification approach

The proposed approach to solve this sensor data-based fault classification problem involves employing an artificial neural network (ANN) model. The choice of a neural network is motivated by its ability to learn complex patterns from data and perform accurate classification. The model used is a sequential model composed of multiple dense layers [7].

The primary step of the approach is to preprocess the data by dividing the temporal sequences into smaller segments using a sliding window. This allows capturing local information about the faults and facilitates the model's learning process. Class labels are encoded using one-hot encoding to enable multi-class classification. Next, the neural network model is constructed by defining dense layers with ReLU activations. The last layer uses softmax activation for multi-class classification. The "Adam" optimizer is employed for adjusting the model's weights during training, and cross-entropy loss is employed as the loss function to evaluate the difference between predictions and true class labels [7].

The model is then trained on the training data using batch training techniques. The model's performance is evaluated using accuracy metrics and the confusion matrix.

The confusion matrix helps assess the model's performance for each fault class, identifying false positives and false negatives.

For data visualization, a t-SNE dimensionality reduction technique is employed to project the data representations into a two-dimensional space. This allows visualizing clusters and structures in the data, which can aid in result interpretation.

CNN classification approach

The proposed approach for solving this sensor data-based fault classification problem involves using a convolutional neural network (CNN) model. The choice of a CNN is motivated by its ability to capture spatial and temporal patterns in the data, which is essential for sequence classification [7].

The initial stage of the methodology is to preprocess the information by segmenting the temporal sequences into smaller segments using a sliding window. This allows capturing local information about the faults and facilitates the model's learning process. Class labels are encoded using one-hot encoding to enable multi-class classification.

Next, the CNN model is constructed by defining convolutional and pooling layers. The convolutional layers are responsible for extracting features from the data, while the pooling layers reduce the dimensionality of the data. ReLU activations are used to introduce non-linearity into the model. After the convolutional and pooling layers, the extracted features are flattened and fed into dense strata. The dense strata are accountable for the final classification of the data. The last layer uses SoftMax activation for multi-class classification. The "Adam" optimizer is used to adjust the model's weights during training, and cross-entropy cost serves as the loss function to evaluate the difference between predictions and true class labels.

The model is then trained on the training data using batch training techniques. The model's performance is evaluated using accuracy metrics and the confusion matrix, similar to the previous approach.

For data visualization, t-SNE dimensionality reduction technique can also be used to project the data representations into a two-dimensional space.

Analysis of training results: This step involves examining the performance of the model during training by analyzing accuracy and loss curves over epochs. These curves offer valued visions into the model's advancement, aiding in the identification of potential issues such as overfitting or underfitting.

Confusion matrix evaluation: The confusion matrix is used to evaluate the model's performance in more detail. It quantifies the number of correct and incorrect predictions for each failure class allowing for the calculation of precision rates per class. This matrix highlights the best and worst-performing categories.

Interpretation of t-SNE results: The t-Distributed Stochastic Neighbor Embedding (t-SNE) algorithm is employed to reduce the dimensionality of data and facilitate visualization.

The results obtained from the analysis are interpreted to extract insights regarding the distribution and patterns present within the data.

4. Results and discussions

Our system was tested and validated in a clinic (Clinique d'Oncologie 16 novembre), the data being a vibration collected from three motors: the BRM motor, the compressor, and the Water CHILLER. The compressor frequency is shown in figure 4.

Based on the extracted data, we can determine the motor's rotational frequency, which corresponds to the fundamental frequency F = 75 Hz for velocity calculation. The code was used to preprocess and analyze the vibration data for this motor.

The previously mentioned steps were applied to calculate the RMS values.

To comply with the ISO 10816 standard, several steps were performed in the project. Firstly, vibration data from the motor was collected using appropriate sensors. These data were then processed and analyzed following the methodology described earlier.

The ISO 10816 standard was applied to three different motors: a compressor, a BRM chiller, and a water chiller. Each motor underwent a similar methodology for acquiring, processing, and analyzing the vibration data specific to that motor.

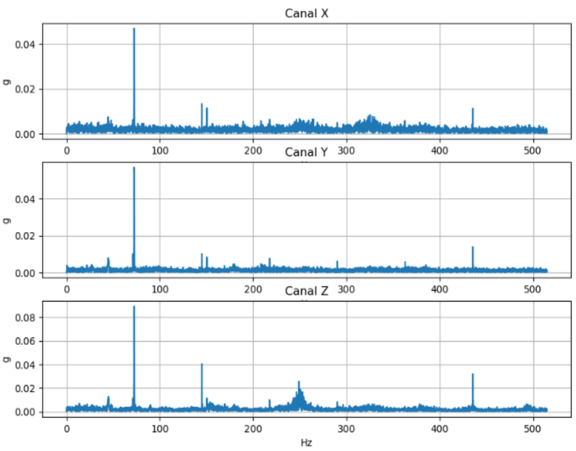

Fig. 4. The frequency spectra of compressor

Table 2. Vibration values data frame

	Axis	Vibration (mm/s)
0	Axis X	2.851490
1	Axis Y	2.865342
2	Axis Z	2.276412
3	Average	2.664415

Our program utilizes the AES symmetric encryption algorithm to provide file encryption and decryption functionality. It consists of two main functions: encrypt File and decrypt File. In the encrypt File function, a password is used to generate an encryption key, and AES encryption is applied to the file content using CBC mode and an initialization vector. The encrypted file is saved, and the execution time is measured. The decrypt File function reverses the process by using the provided password, initialization vector, and AES decryption to obtain the original file. The code handles command-line arguments, verifies their validity, and executes the corresponding function accordingly. The fundamental principle is to secure file content using AES encryption with a derived key. CBC mode ensures security and appropriate block size, while performance is evaluated by measuring execution time.

Our AES-based security program provides an effective solution for ensuring the confidentiality of data during transfer over a secure network. The conducted tests have confirmed the robustness and performance of our program. By utilizing this tool, you can guarantee the security of your sensitive files during transmission.

- ANN classification: Analysis of training results

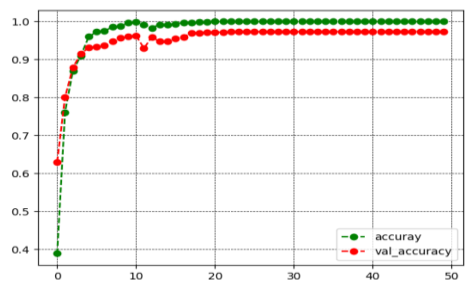

Fig. 5. Analysis of training results for ANN

- Confusion matrix evaluation

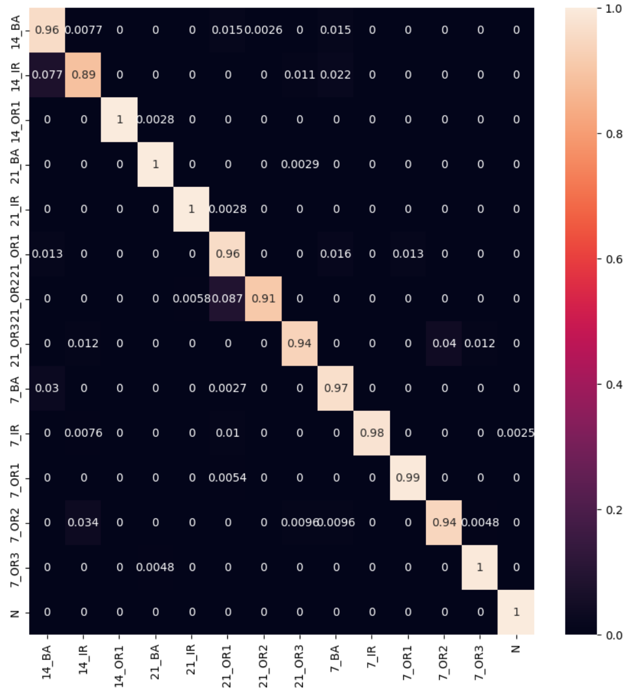

Fig. 6. *Confusion* matrix *evaluation* for ANN

- CNN classification: Analysis of training results

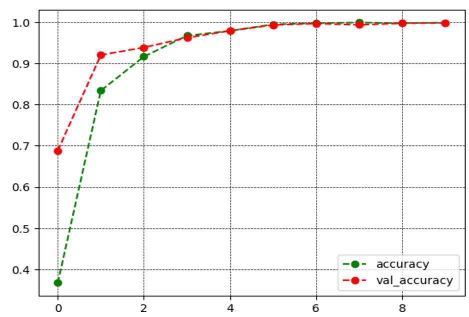

Fig. 7. Analysis of training results for CNN

- Confusion matrix evaluation

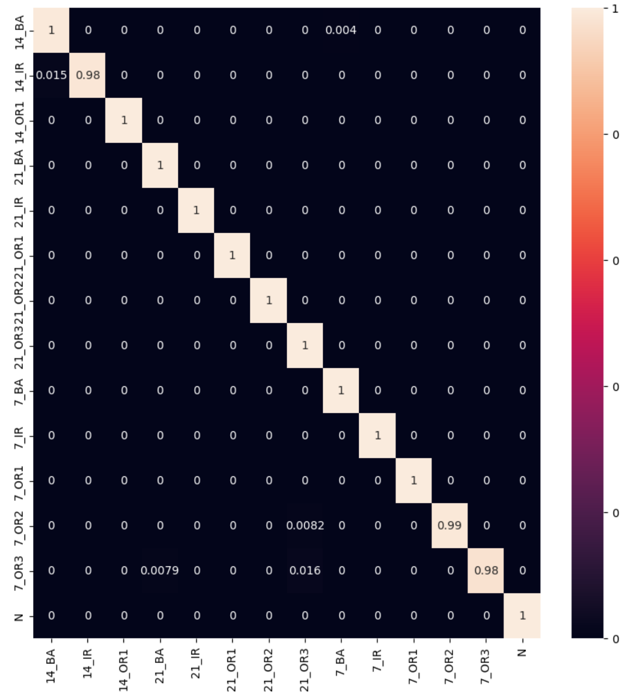

Fig. 8. Confusion matrix evaluation for CNN

- Interpretation comparing the two models

In this study, two models were compared: a convolutional neural network (CNN) model and a one-dimensional neural network (ANN) model. This comparison allowed for the evaluation of their respective performances and determining which model offers better prediction of failure data.

As shown in figures 7 and 8 the results reveal that the CNN model exhibits a higher overall accuracy (more than 98%) compared to the ANN model as follows in figures 5 and 6. When examining the accuracy curves during training, it is observed that the CNN model achieves higher accuracy for both training and validation data compared to the ANN model. This indicates that the CNN model is better able to capture the patterns and structures within the data and generalize its predictions.

5. Conclusion

In this work an advanced monitoring system has been developed. The results obtained show that the predictive maintenance solution for MRI pumps based on IOT, offers promising prospects for enhancing the availability and efficiency of these critical medical devices. The system gives a real-time data collection and recording of vibration data, coupled with AI techniques for analysis and classification. The application of IoT enables precise visibility into the condition of MRI pumps through real-time collection of vibration data. Leveraging AI models for instance convolutional neural networks (CNN) and artificial neural networks (ANN), the system successfully predicts and classifies vibrations based on their criticality level. It enables targeted preventive maintenance and informed decision-making to prevent failures or unexpected breakdowns. Additionally, the implementation of an AES-based encryption protocol ensures data security throughout the transmission process. It safeguards the confidentiality of sensitive information and it preserve data integrity, by bolstering trust in the overall system.

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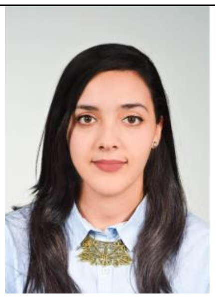

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