Predictive Maintenance for a Industrial Robotic Arm using LoRa Technology

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***Abstract*—Industrial Internet of Things (IIoT) systems enable businesses to monitor and analyze their equipment in real-time to prevent breakdowns and optimize performance. Predictive maintenance is a crucial part of IIoT systems.Industries can foresee probable equipment breakdowns, save downtime, and boost overall equipment effectiveness by using Long Range (LoRa) technology in predictive maintenance.LoRa technology provides long-range, low-power connectivity for IIoT devices, making it an excellent option for predictive maintenance applications. The potential of LoRa-based predictive maintenance systems in the IIoT will be examined in this paper.This survey offers a thorough review of LoRa-based predictive maintenance in the IIoT.Finally, we'll go over several research papers and actual examples of LoRa-based predictive maintenance implementations.**

Index Terms—Predictive Maintenance; Industrial Internet of Things(IIoT); LoRa Technology; Machine Learning.

I. Introduction

According to [1], the word "Internet of Things" (IoT) refers to a network of real, physical objects or devices that are connected to the internet and are capable of communicating with one another without the aid of a person. These products can include everything from wearable technology, household appliances, and smart thermostats to office supplies and cars.Based on information collected from sensors and other sources, predictive maintenance [2] is a proactive approach to maintenance that entails forecasting when machinery or other equipment is likely to fail. This strategy is gaining popularity in the industrial internet of things (IIoT) because it enables businesses to prevent unplanned downtime and lower maintenance expenses.According to the search here [3] The term IIoT refers to the usage of networked sensors, machines, and devices in industrial settings. IIoT is a subset of the larger IoT. Real-time monitoring and control of industrial processes are made possible by the IIoT.The perception layer, which has sensors for perceiving and gathering environmental data, is the perception layer.The task of connecting to other intelligent devices,network elements, and servers fall under the purview of the network layer.The user-facing provision of application-specific services is the duty of the application layer.

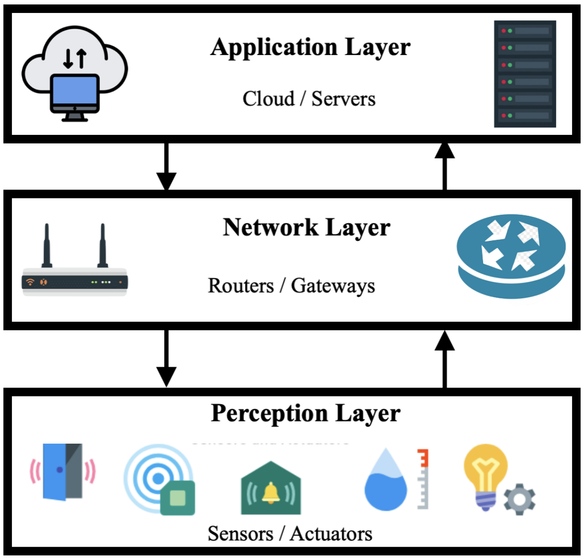

Figure 1:- Generic Three Layer IoT Architecture

II. LoRa Architecture

In accordance with the research here [13] three essential parts make up the LoRa architecture.Each of these elements is essential for enabling low-power, long-distance communication between devices.
End devices: These are the gadgets that perceive their surroundings and gather information. Data packets from end devices are transmitted to adjacent gateways using LoRa modulation.
Gateways: Data packets from end devices are received by gateways, which then transmit them to network servers through a wired or wireless backhaul.
Network Servers: The devices that control the LoRa network and take care of data routing, security.Overall, this architecture supports extensive IoT deployments and enables long-range, low-power communication between devices. It is appropriate for a wide range of applications in sectors including agriculture, smart cities, and logistics since it is scalable, bidirectional,
and secure.

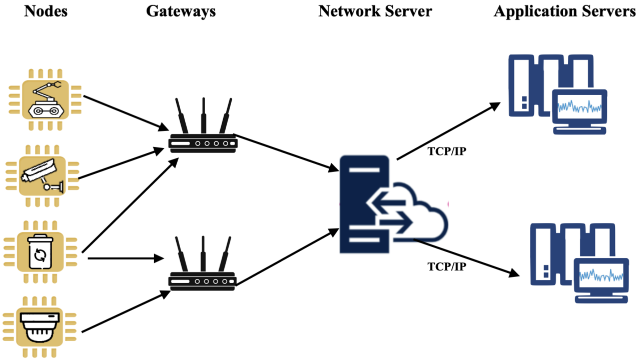

Figure 2 :- A Simple Generic LoRa Architecture

III. State Of The Art

LoRa Wide Area Networks (LoRaWAN), although being in its infancy, have already gained significant recognition.We have surveyed multiple papers starting from the year 2017.Let’s look into all those works to understand how LoRa technology can be helpful in this era of industry 4.0 using predictive maintenance.

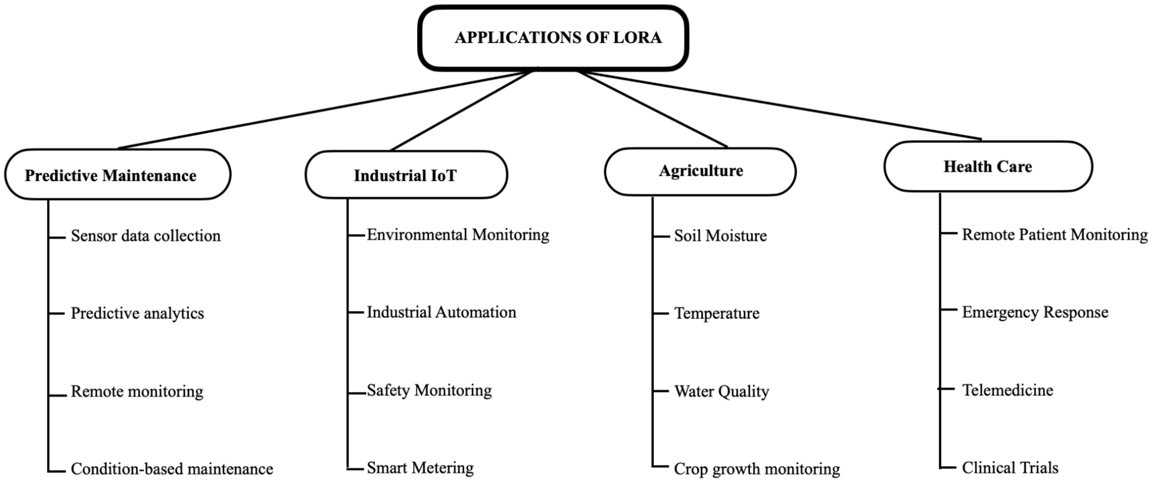

Figure 3 :- Taxonomy of Application of LoRa

Here the authors of [3] talks about the issues that LoRa and LoRaWAN (Long Range Wide Area Network) still face are described together with a SWOT analysis of the strengths, weaknesses, opportunities, and threats.Authors provided a semantic review by categorizing research that concentrate on physical level performance and network level performance.They also included IoT

In this work here [4], authors have demonstrated the coverage and performance outcomes for an LPWAN indoor deployment using just one network server and one gateway, we set up a LoRaWAN network.Measurements were taken in a true indoor industrial setting.The measurements reveal that we can only cover an indoor area of about34000 meter square with a single LoRa gateway when the spreading factor is 7.

This work here [5], talks about two of the most popular Low Power (LPWAN) technologies.They presented a thorough analysis of NB-IoT and LoRa as effective methods for tying the devices together. The LoRaWAN network uses an adaptive modulation approach in conjunction with a multichannel multi-modem transceiver in the base station to accomplish the task.

The authors of this work [6] discussed a novel wireless protocol that was appropriate for advanced manufacturing and the Internet of Things (IoT).

In this work here [7] authors concentrated on LoRaWAN, and provided an evaluation of its performance for typical IIoT employments.They go over how to adjust a few of its parameters to get the optimum performance in the hypothetical industrial setting.Moreover, they have proposed a comparison of LoRa with the IEEE 802.15.4 network protocol which can be used in similar contexts.

The authors of this study [8] described the design and implementation of a real-time monitoring and troubleshooting system based on LoRa-based wireless sensor networks (WSN) technology.For system diagnostics, troubleshooting, and preventive maintenance, their suggested system comprises of LoRA-based wireless motes that wirelessly transmit summary data in real-time to a developed monitoring software interface.For the goal of troubleshooting, data were collected from both healthy and problematic machines.

In the work here [9] the author focuses on challenges faced by the wireless communication signals due to its industrial use in severe conditions, including noise, interference, etc., which lowers service quality.Authors performed node trials utilising the WaterGrid- Sense, a brand-new LoRa-based full-stack sensor node for IWSN.

The authors of this article [10] contend that the adoption of LoRa, which is similarly promising for Industrial Internet of Things (IoT) scenarios, is constrained by the applicable standardized MAC protocol, LoRaWAN, which cannot manage real-time data flows. They proposed RT-LoRa, a medium access strategy for LoRa that supports real-time flows, in order to create LoRa-based LPWAN for industrial IoT applications.The research explains RT-LoRa, offers some tips for setting up an RT-LoRa network, and displays a simulative analysis in a believable industrial IoT scenario.

TABLE I. APPLICATION DOMAIN

Reference & year	Application Domain
[5] 2017, [4] 2017 , [3] 2018, [7] 2018, [9] 2019, [10] 2019, [15] 2019, [20] 2021, [25] 2022	IoT & IIoT
[13] 2020, [27] 2023	Predictive Maintenance
[16] 2020	Behaviour Prediction
[19] 2021	Industrial Parameter Monitoring
[21] 2021	Industrial Maintenance
[23] 2021	Real-time IoT systems
[25] 2022	Fog Computing-based Predictive Maintenance
[18] 2020	IoT & Telecommunication Industry
[17] 2020	IIot & Cloud Computing

Authors in this work [11] provided the technical difficulties of setting up LoRa networks and current fixes. Several of the unresolved problems of LoRa networking are discussed based on their thorough research of existing solutions.They proposed that A heuristic method is used by the joint decoding algorithm to choose the signals that will be integrated in the cloud.As per their findings the conventional LoRa technology has enhanced battery life and range by three.

Three main problems with current wireless automation systems have been recognised by the authors here [12]: a small wireless communication range, inadequate or nonexistent data transmission security, and high energy consumption of battery-powered remote data gathering devices. In order to overcome these limitations, they suggested and created a special low power LoRa-based flexible hardware architecture for use in industrial remote monitoring and control. By obtaining a LoS (Line of Sight) capability, they even outperformed the capabilities of the most advanced systems currently in use.

In this work here [13] does a good job of laying out some of the LoRa applications for predictive maintenance. To prove LoRa's superiority the precise hardware specifications and testing findings are provided by the authors.Any anomalies and these data can be down-streamed and then placed via a machine-learning-powered prediction technique, which permits us to detect the malfunctioning status of the equipment.

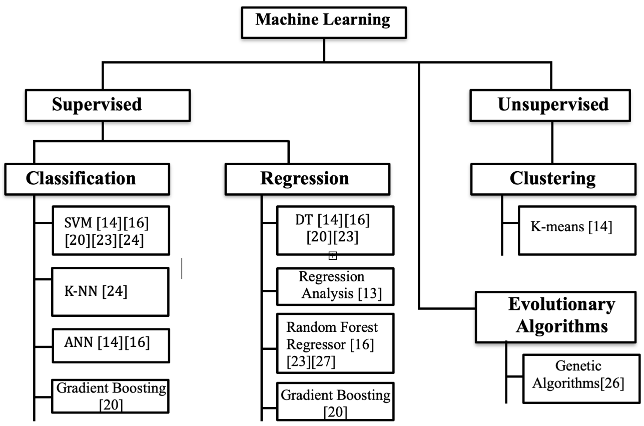

Figure 4 :- ML Algorithm Classification

The work in here [14] gives an overview on the use of machine learning techniques for the wireless Internet of Things (IoT).The paper discusses several machine learning methods and their uses in wireless Iot, including neural networks, decision trees and Support Vector Machines (SVM).

The work in here [15] outlines an innovative strategy to improve LoRaWAN's functionality for industrial IoT applications.Authors suggested method, known as TS-LoRa, uses time slotting to arrange transmissions and lessen collisions, enhancing network performance as a whole.
The study here [16] outlines how LoRaWAN, a young technology in the Internet of Things (IoT) industry, can be enhanced through the application of machine learning. The authors offer a method for handling LoRaWAN packets and show how to use machine learning to profile devices and foresee the inter-arrival of IoT packets.
Authors in work here [17] suggested gateway includes a smart agent that controls device connectivity, coordinates polling, decodes packets, and periodically passes unified data to applications using public or private cloud services.The suggested gateway provides easy access long-range connectivity for a variety of industrial applications.
The study here [18] covers the expanding usage of low-power wide area network technologies.The suggested framework may operate an IoT application as a 5G network and application lifecycle management features.
The research presented here [19] examines how LoRa (Long Range) technology, which permits low-power wireless communication over vast distances, can be used for industrial parameter monitoring. The writers talked about how LoRa is more affordable, has a greater range, and lasts longer than other wireless technologies. A case study of how LoRa was used to monitor storage temperature and humidity is also provided by the authors. The authors claim that LoRa is a hopeful technology for tracking industrial parameters and that it can be used for many different things, such as asset tracking, smart farming, and environmental monitoring.
The work here [20] introduces the Industrial Internet of Things (IIoT) infrastructure for predictive maintenance known as TIP4.0.Authors used machine learning techniques to evaluate this data in order to find patterns and abnormalities that might point to equipment malfunctions or problems.
The work here [21] focuses on using Industrial Internet of Things (IIoT) technologies to apply predictive maintenance methods in industrial settings, and examines the advantages and difficulties of doing so. According to the authors, conventional maintenance techniques like corrective and preventive maintenance are frequently reactive and might result in unanticipated downtime and production losses.
The authors here[22] emphasize the importance of the communication protocols used by IoT devices as well as the need for security measures to protect against possible online threats. Additionally discussed is how sensors and actuators work in IoT applications. The article provides a thorough analysis of the core concepts and technological advancements behind IoT-based industrial automation.
The work here [23] offers a list of difficulties ML algorithms face in IoT systems, such as the lack of enough processing resources, the heterogeneity of the data, and security issues. In order to address these issues and raise the effectiveness and efficiency of IoT systems, ML techniques are reviewed.
In the study here [24], authors suggest a system that transmits data using LoRa technology, which is subsequently gathered by a gateway and sent to a centralized monitoring system for analysis. The system monitors temperature, humidity, and pressure, in an industrial setting.The system also uses SVM and K-Nearest Neighbour (KNN) to detect whether the machine is at fault or not.

TABLE II. LIST OF ML ALGORITHMS USED

Reference & year	**ML Algorithm Used**
[13] 2020	Regression Analysis
[14] 2020, [16] 2020, [20] 2021, [23] 2021, [24] 2022	SVM
[14] 2020, [16] 2020, [20] 2021, [23] 2021,	Decision Trees
[14] 2020, [16] 2020,	ANN
[16] 2020, [23] 2021, [27] 2023	Random Forest Regressor
[25] 2022	PSO (Principle Swarm Optimisation)
[26] 2023	Genetic Algorithm
[21] 2021	Microsoft Azure Machine Learning.
[20] 2021	Gradient Boosting

The authors here[25] use machine learning methods to analyze network data and optimize network parameters like spreading factor and transmission power in order to decrease packet loss and improve overall efficiency of the LoRa network. The results show that the machine learning strategy significantly improves network performance.
The works presented here [26] propose a predictive maintenance approach for effective asset management in Industry 4.0 using IoT and cloud computing technologies. The programme analyzes data collected from sensors built into industrial machinery to anticipate maintenance needs. The fog computing layer is developed to address the issues with data processing and storage in IoT-based systems. The suggested model aims to increase equipment uptime and cut maintenance costs in order to increase the overall efficacy of industrial operations.The writers support the proposed model and demonstrate how accurately it predicts maintenance needs. The significance of ongoing research in this field is emphasized in the paper's conclusion, as well as the possibility of the proposed model being used in other industries.
According to the work presented here [27], this research covers the construction of a Predictive Maintenance system for industrial machines using the Internet of Things (IoT) and the Random Forest Regressor algorithm. In order to reduce downtime and increase productivity, the system's goal is to predict the likelihood of a machine breakdown and schedule maintenance tasks appropriately. They collected data from different sensors mounted on the machines as well as how the information is prepared and fed into the Random Forest Regressor model for forecasting. The model is evaluated based on a number of factors, and the results show that the system is very good at forecasting machine failure and the Remaining Useful Life [RUL].

TABLE III. TECHNOLOGY STACK AND MOTIVATION

Reference & year	**Tech Stack**	**Limitation**
[3] 2018, [7] 2018, [15] 2019, [16] 2020	LoRaWAN	[3] [15] Increase power consumption [7] Limited comparison with IEEE 802.15.4 [16] Impact of external factors
[5] 2017, [25] 2022	LoRa & NB-IoT	[5] Simulation
[17] 2020, [20] 2021, [21] 2021, [23] 2021, [27] 2023	MQTT	[17] The single-channel LoRa gateway is limited [20] Regarding the supported operations [21] Eventual incorrect predictions [23] Challenging implementation of ML models in resource-constrained IoT devices [27] Simulation
[18] 2020	ETSI MEC (Multi-access Edge Computing) framework	[18] Simulations
[10] 2019	RT-LoRa	[10] Increased the communication reliability
[4] 2017	MATLAB and LoRa technology for wireless communication	[4] complexity,security
[9] 2019	LoRa Radio	[9] Simulation
[19] 2021	Azure IoT, AWS IoT and LoRa technology for wireless communication	[19] Limited bandwidth and low data rate
[24] 2022	LoRa and Thingspeak	NA
[26] 2023	FogWorkflowsim	[26] Scalability

IV. Proposed Methodology

No_of_Position	Speed	Seconds	Temperature	Target
5	200	0.8669950739	57	1
5	200	0.8663366337	62	1
5	200	0.8712871287	49	0
5	200	0.8712871287	47	0
5	200	0.8712871287	48	0

Figure 5 :- Dataset

The data was gathered by operating the robot for 6-7 hours, incorporating various positions and speeds. Temperature measurements were recorded, and the average seconds were calculated. The target value was determined based on the threshold of the average seconds.

```
# Input:
#   - Load the dataset from 'C:/Users/PRAJWAL_PC/Downloads/Dataset_Robo.csv'
#   - Specify column names if needed
#   - Choose SVM kernel ('rbf')
#   - Set random seed for reproducibility (random_state)
#   - Define train-test split ratio (train_size)
#   - Specify target column name ('Target')

# Output:
#   - Trained SVM model
#   - Evaluation metrics (accuracy, confusion matrix, classification report) on both training and test sets
# Processing:

# Load the dataset
df = LoadDataset()

# Train-test split
train_set, test_set = TrainTestSplit(df, train_size=0.75, random_state=1)

# Initialize SVM classifier with 'rbf' kernel
classifier = InitializeSVMClassifier(kernel='rbf', random_state=1)

# Train the SVM model on the training set
TrainSVMModel(classifier, train_set_X, train_set_y)

# Make predictions on the training set
svc_y_pred_train = PredictUsingSVMModel(classifier, train_set_X)

# Output the results (accuracy, class distribution percentages, etc.)
OutputResults(accuracy_train, abnormal_percentage_train, normal_percentage_train, accuracy_test, abnormal_percenta
```

Figure 6 :- Pseudocode of SVM Model

Data Preparation: We used a train & test split to divide your dataset into training and test sets after loading it from 'Dataset_Robo.csv'.After the features were chosen, train_set_X and test_set_X were given the input features, and train_set_y and test_set_y were given the target labels.
Model Training:We chose the Radial Basis Function (RBF) kernel for your SVM (SVC(kernel='rbf', random_state=1)) and trained it on the training set.
Model Evaluation on Training Data: Using the training data, you generated predictions (svc_y_pred), and we used accuracy_score to determine the accuracy.
Class Distribution Analysis: To determine how to balance "abnormal" and "normal" classes, we examined the distribution of classes in your training set.
Evaluation of the Model Using Test Data: Using the test data, we made predictions (svc_test_y_pred), and you computed the accuracy, confusion matrix, and classification report.

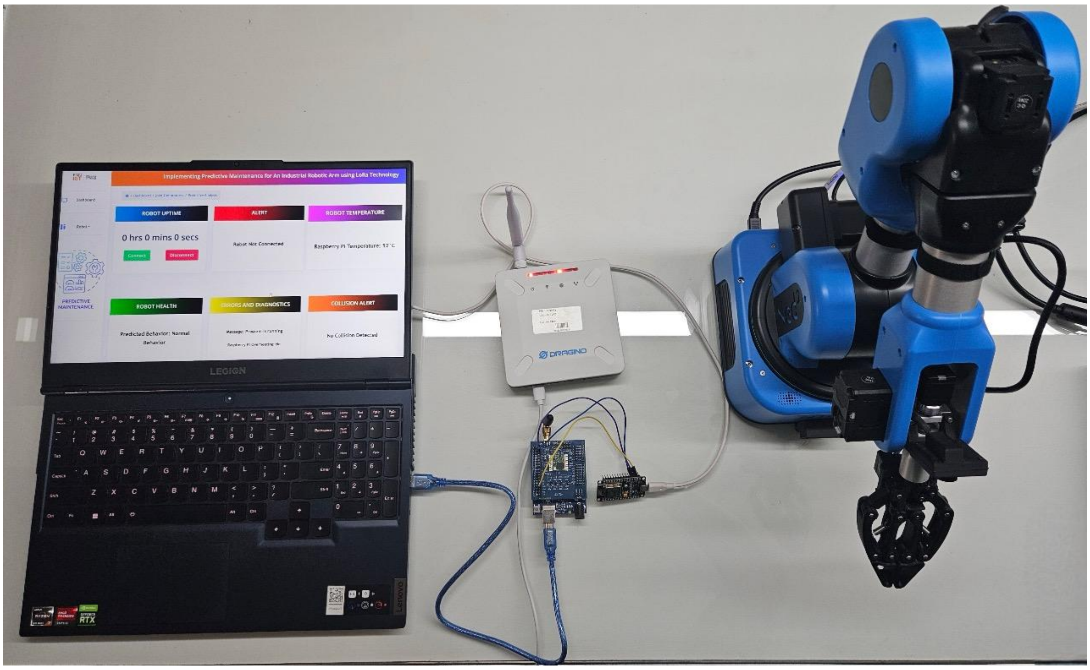

Figure 7 :- Test Bed Setup

Figure 5 illustrates the test bed setup employed for conducting predictive maintenance on the robotic arm. The arm is powered on and assigned a task, which we recorded by capturing data from the rostopics. We determined the average duration of one arm movement and established it as a threshold value for surpassing the average seconds.The Robot Operating System (ROS) offers various rostopics that continuously publish robot data. We subscribed to these rostopics to extract the necessary information. The collected data is transmitted to an ESP8266 WiFi module through an MQTT broker. The ESP8266 then forwards the received data to an Arduino Uno via a serial connection, as depicted in Figure 5.Subsequently, the Arduino Uno transmits the data to a LoRaWAN gateway, utilizing APPKEY, APPEUI, and DEVEUI, which are obtained by registering the LoRaWAN gateway with The Things Network (TTN). The received data can be visualized in the TTN console.To feed this data into our machine learning (ML) model, we leverage TTN's MQTT integration. Our ML model subscribes to the MQTT topic of TTN, where the data is published, enabling it to predict whether the observed behavior is normal or abnormal.

V. Results

Figure 8 :- Sending data to LoRa Gateway

The information above demonstrates how to use an AppKey and NetworkKey to send data to the LoRa Gateway.Every time data is sent to Arduino, a packet is queued up for transmission to TTN.

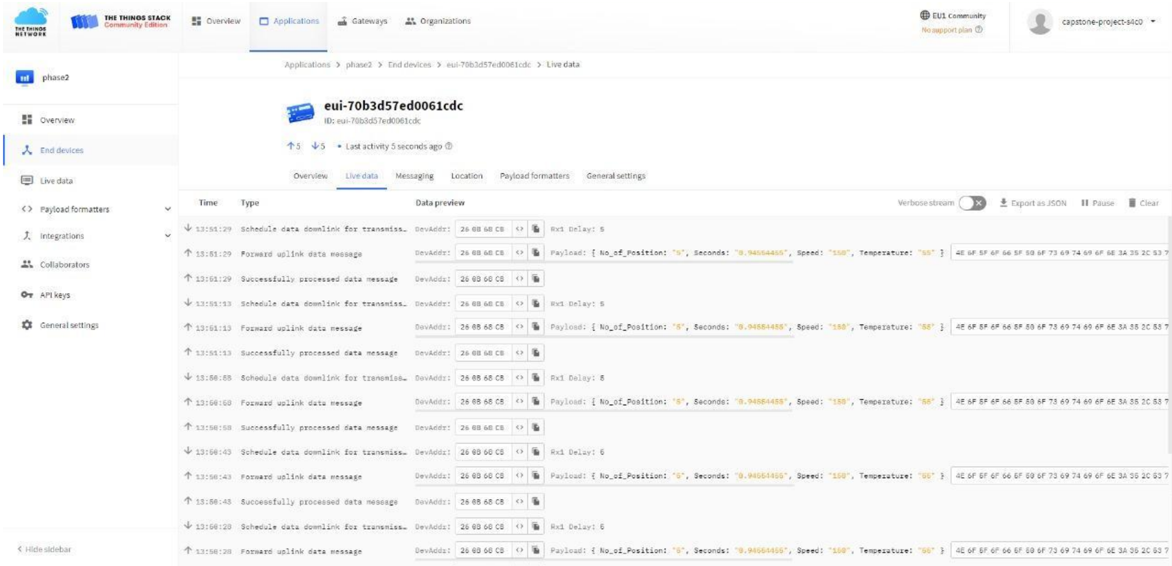

Figure 9 :- Data Recieved on TTN

The information above demonstrates how to use an AppKey and NetworkKey to send data to the LoRa Gateway.Every time data is sent to Arduino, a packet is queued up for transmission to TTN. Data is being received from Arduino, as shown in Figure 7.3, and the payload formatter has been set up to match the expected data.

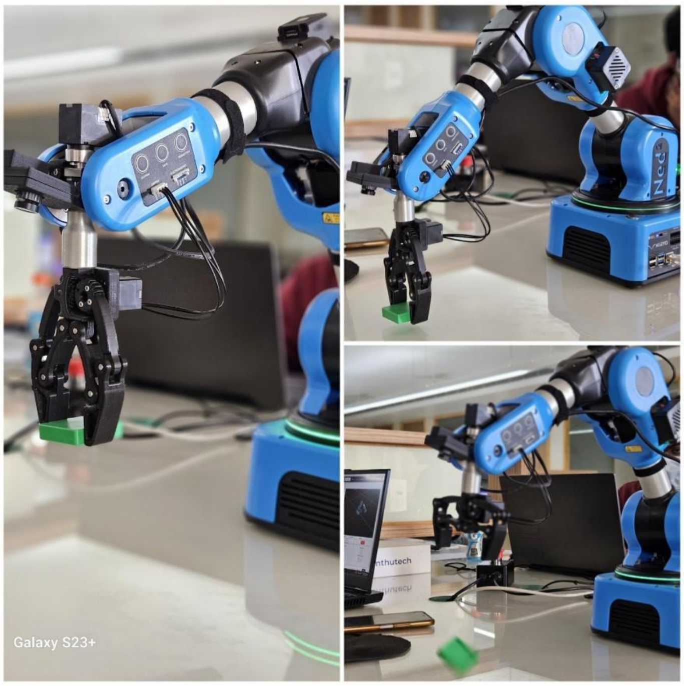

Figure 10 :- Pick, Intermediate & Place Position

Pick Position: The robot moves toward the object and positions its end effector to grab or lift it. **Intermediate Position:** The robot may move to an intermediate position after picking up the object. This could be a stage of transition, giving room for modifications or getting ready for the next move.**Place Position:** The last phase involves the robot precisely moving to the predetermined spot in order to release or place the object.

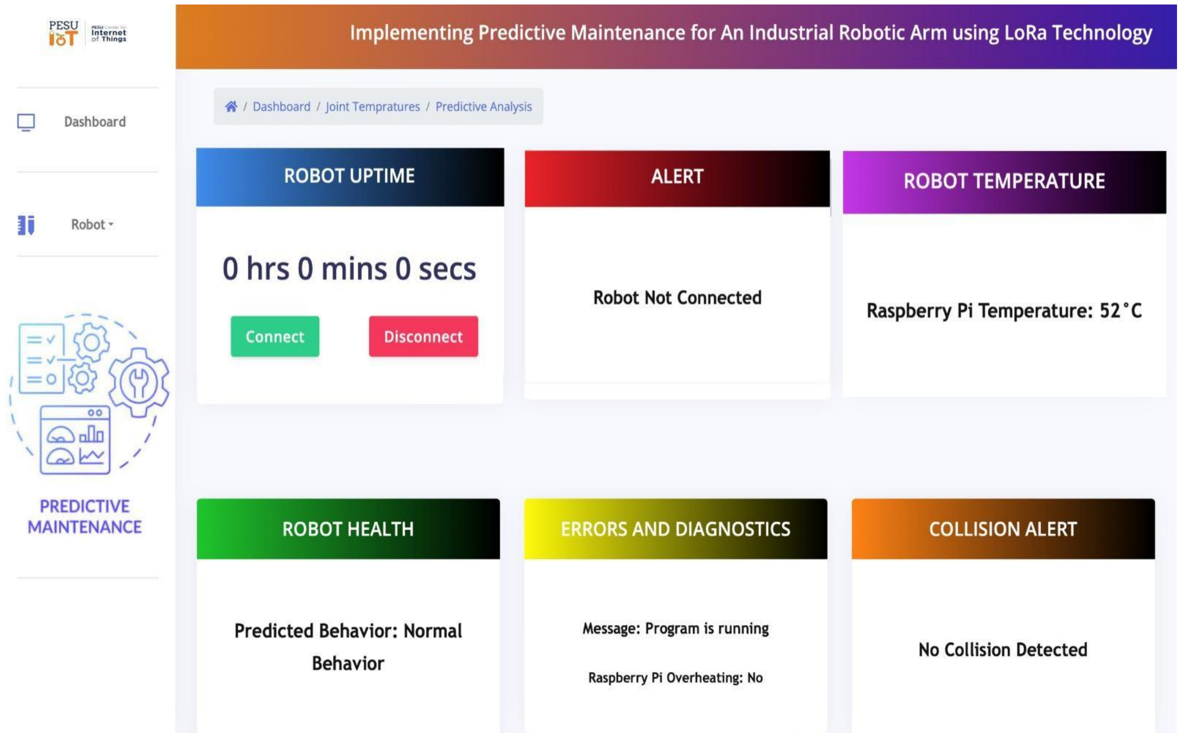

Figure 11 :- Dashboard

The dashboard shows information about the Collision Alert, Robot Temperature, Robot Health, Errors and Diagnostics.

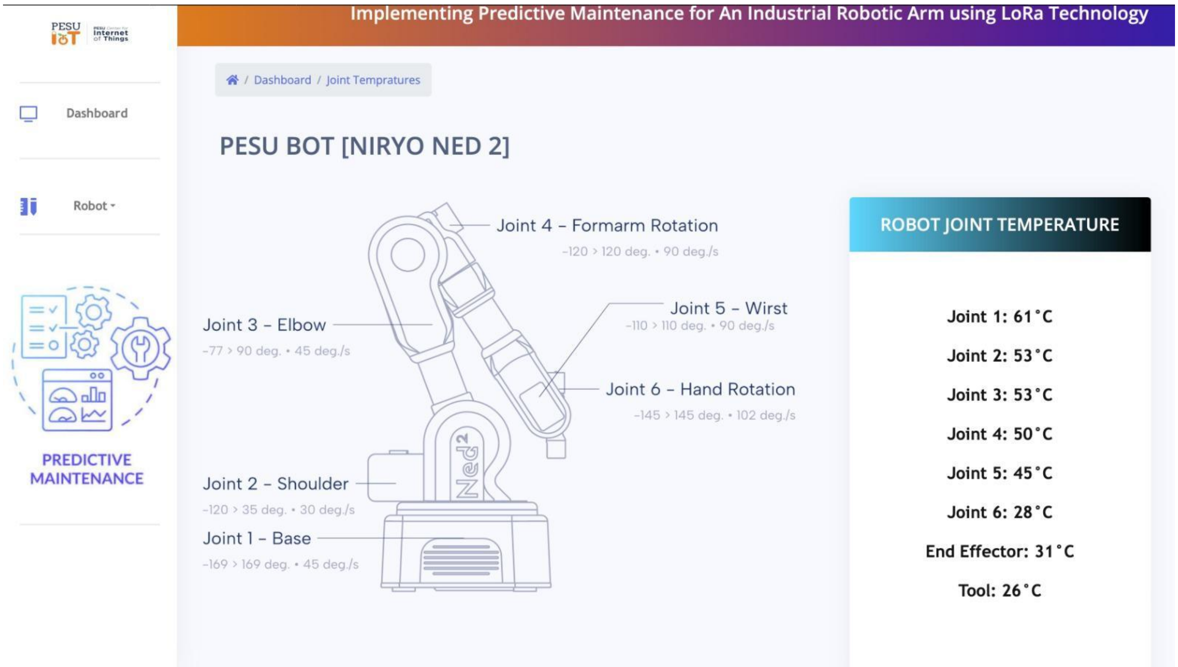

Figure 12 :- Joint Tempratures

The six joints that make up the Niryo 2 robot arm are all outfitted with temperature sensors. Real-time data on the temperature conditions of these joints is provided by this feature, enabling efficient management and guaranteeing peak performance while operating.

VI. Justification OfResults

```
Accuracy for SVM model on the test data: 97.98%
Confusion Matrix:
[[152   3]
 [  4 188]]
Classification Report:
              precision    recall  f1-score   support

    abnormal       0.97      0.98      0.98       155
      normal       0.98      0.98      0.98       192

    accuracy                           0.98       347
   macro avg       0.98      0.98      0.98       347
weighted avg       0.98      0.98      0.98       347
```

Figure 13 :- Confusion Matrix

To distinguish between the robotic arm's normal and abnormal states and assess accuracy, we are utilizing a confusion matrix.

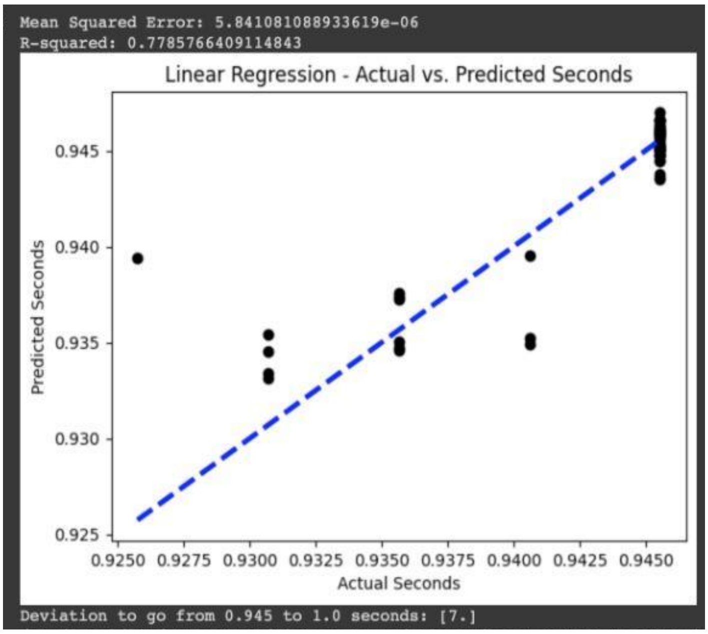

Figure 14 :- Linear regression Graph

We were able to calculate the deviation required to go from 0.945 to 1.0 seconds, as the above figure illustrates.The model accounts for 77% of the variability in the response variable, and the remaining 23% is attributed to other factors not included in the model.

VII. Conclusion

Based on the thorough survey, LoRa technology is a potential option for preventive maintenance in industrial settings. According to the papers analysed, LoRa-based solutions can efficiently monitor industrial equipment and foresee possible problems, which can result in significant cost savings by lowering downtime and maintenance expenses.

The benefits of using LPWAN technologies, such as LoRa, for predictive maintenance in IIoT applications are also covered in the paper.The authors point out that LoRa has a number of benefits over other LPWAN technologies, including low power consumption, long-range connectivity, and affordability, which make it appropriate for IIoT applications.

In IIoT applications, predictive maintenance is essential to maintain continuous and effective operation, increase asset usage, decrease downtime, and optimize maintenance schedules. The study emphasizes how crucial it is to use the right instruments to gather information from various sources, including vibration, temperature, and pressure, so that it can be analysed using various data analytics methods.

The paper emphasises the importance of this field, the role of sensors and data analytics, and the advantages of LPWAN technologies like LoRa while providing a comprehensive analysis of the state-of-the-art in LoRa-based predictive maintenance for the IIoT. It is very beneficial to have the authors' perspectives on current research trends and possible future directions for predictive maintenance in IIoT using LoRa.

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