CHAPTER 1

Introduction

Recent years have seen a tremendous evolution of the manufacturing sector, and new technologies are continuously being developed to increase operational effectiveness. Predictive maintenance is one such technology that uses data from equipment to forecast when repair is necessary. Manufacturers may minimize downtime, lower maintenance costs, and boost overall productivity by employing predictive maintenance. We will investigate the application of predictive maintenance for an industrial robotic arm utilising LoRa technology in this research report.

The term "Internet of Things" (IoT) describes how common objects are connected to the internet so they may send and receive data. The usage of IoT technologies in industrial contexts, such as manufacturing plants, is known as the "Industrial Internet of Things" (IIoT). IIoT can be used to track inventory, keep track of equipment performance, and boost overall operational effectiveness.

Manufacturers may gather data from a variety of sensors and devices utilising IoT and IIoT technologies, and then use this data to optimise their operations. This information can be utilised to track inventory, check equipment performance, and boost overall operational effectiveness.

An IoT and IIoT application-specific long-range, low-power wireless communication technology is called LoRa. Spread spectrum modulation, a technique used by LoRa technology, enables low-speed, long-distance communication. This technology is especially helpful in industrial situations where equipment may be spread out or difficult to access.

In the manufacturing sector, predictive maintenance is a technique used to spot possible equipment breakdowns before they happen. Predictive maintenance algorithms can find trends that point to impending failures by examining machine data. Instead of depending on a schedule-based strategy that may result in unneeded maintenance or unscheduled downtime, this data can be used to schedule maintenance tasks in a proactive manner. Predictive maintenance aims to maximize equipment uptime while cutting down on maintenance expenses. By spotting problems early and fixing them before they become serious, predictive maintenance can also assist in extending the life of equipment in addition to reducing downtime. Manufacturers may get information from a variety of sources, such as equipment performance, ambient conditions, and inventory levels, by connecting sensors and devices with LoRa technology.

In conclusion, LoRa technology-based predictive maintenance is a successful strategy for maximizing equipment uptime and lowering maintenance costs in the industrial sector. Manufacturers may prevent equipment problems from happening by employing IoT and IIoT technologies to gather data from a variety of sensors and devices, which reduces downtime and increases equipment life. For industrial IoT and IIoT applications, LoRa technology offers a long-range, low-power communication option. Using LoRa technology, manufacturers can implement predictive maintenance to increase operational effectiveness and stay one step ahead of the competition.

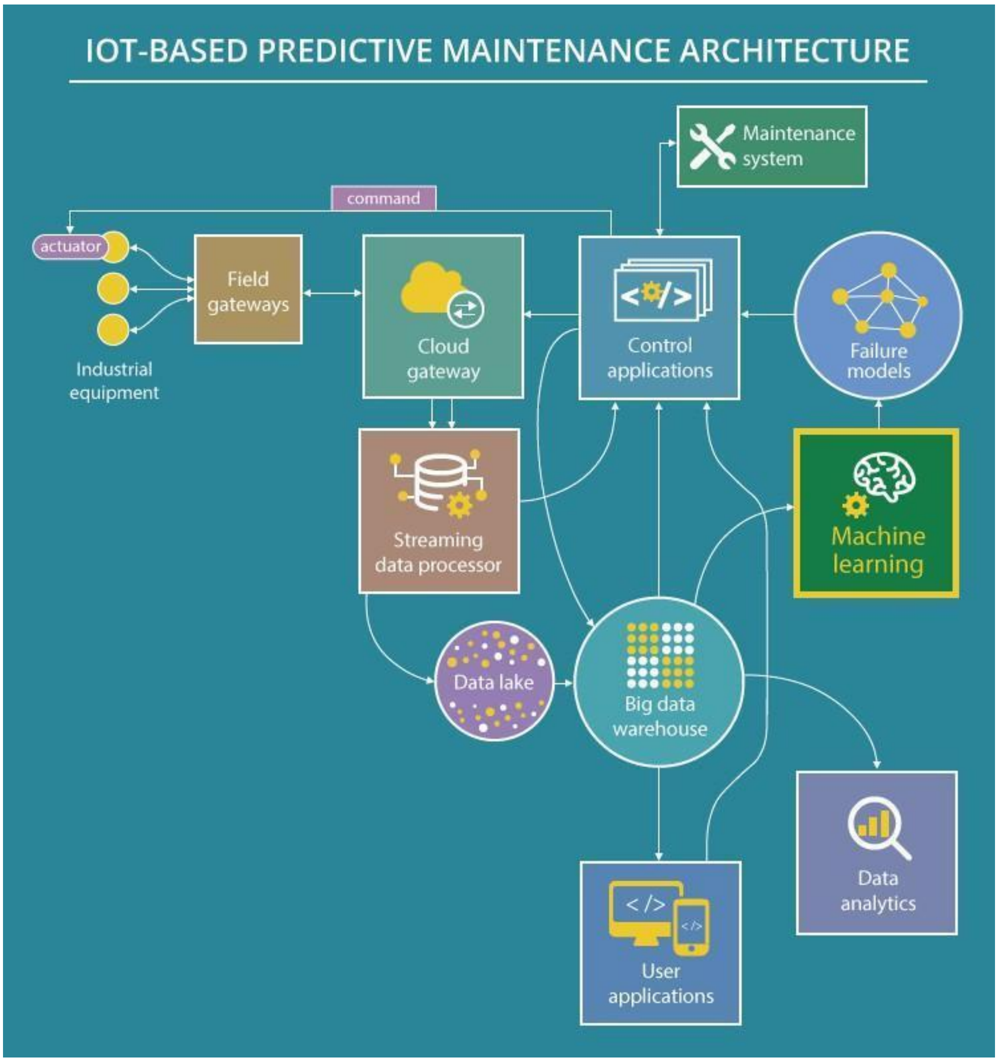


Figure 1.1: - IoT Based Predictive Maintenance Architecture

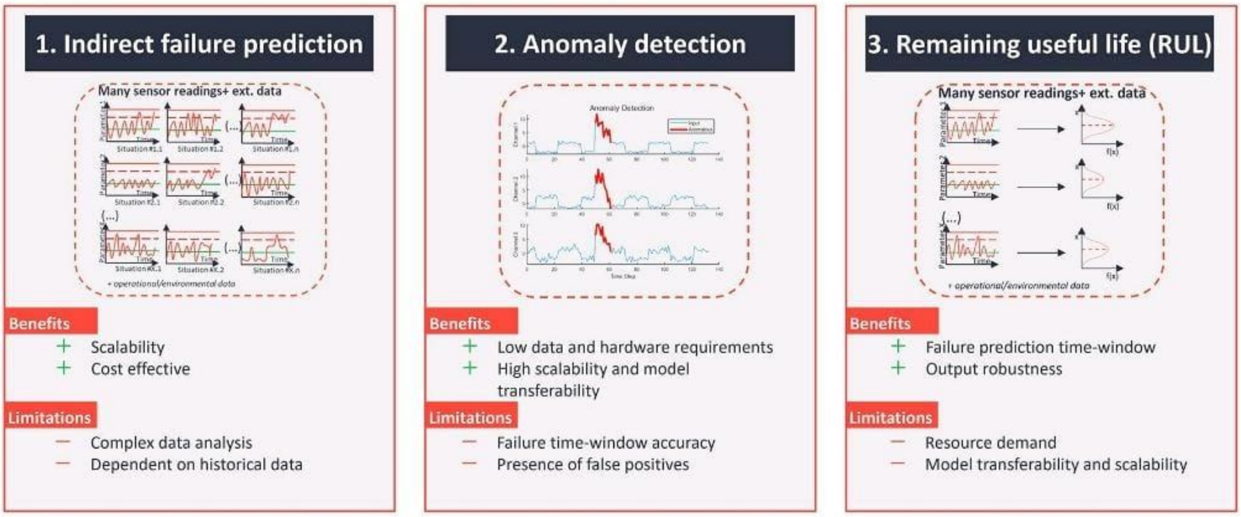


Figure 1.2: - Different Predictive Maintenance Types

The primary distinctions between these are found in their goals, data analysis techniques, and informational/output types. Due to resource constraints and scaling-related environmental issues, RUL is the most challenging to achieve. The most common method has been indirect failure prediction, although anomaly detection is becoming more popular, according to our research.

Figure 1.3: - Market Snapshots

Five significant market features for predictive maintenance as we approach 2024:-

1. The market is estimated to be worth $5.5 billion in 2022, with 17% yearly growth predicted through 2028.

2. There are three varieties of PdM: 1. Anomaly detection techniques are growing; 2. Indirect failure prediction; and 3. Remaining useful life

3. Pre-trained models are one of the six features that PdM software packages have in common.

4. It's becoming more crucial to integrate into the maintenance cycle, particularly with CMMS and APM

5. Effective providers of stand-alone solutions focus on certain sectors or assets, such as particular motors or pumps.

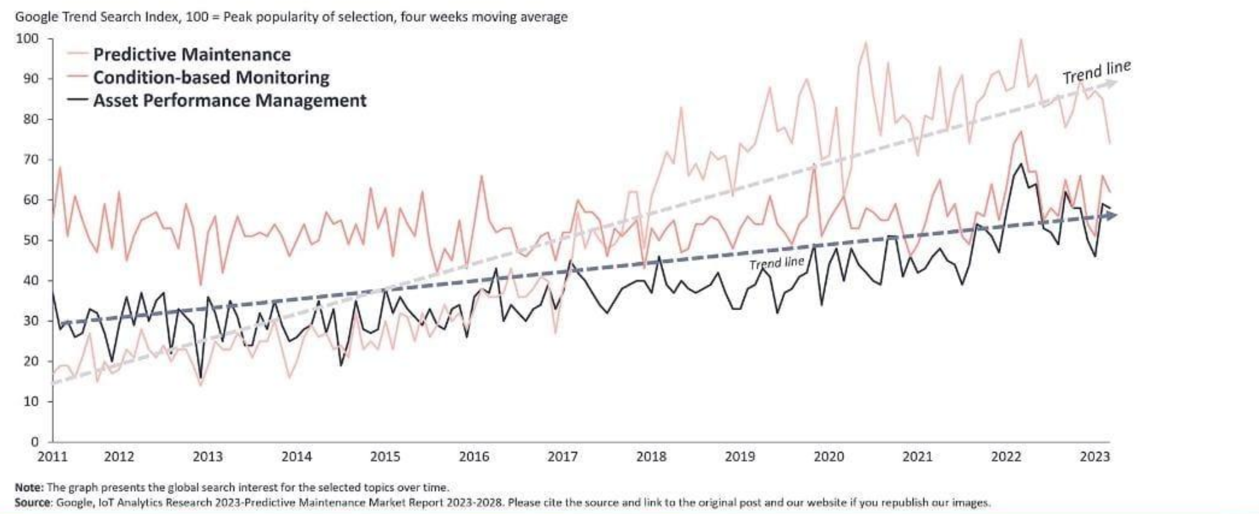


Figure 1.4: - Global Search Interest for Predictive Maintenance

Over the past 12 years, there has been an increase in general search interest in predictive maintenance and associated themes. The word has been more popular online than searches linked to condition-based maintenance and asset performance management (APM), having increased by almost three times since 2017.

CHAPTER 2

Problem Statement

In many production processes, industrial robotic arms are utilized to quickly and precisely carry out repetitive operations. However, they are prone to wear and tear over time, just like any machine, which may cause unplanned downtime and raise maintenance costs. Traditional maintenance procedures are frequently reactive, which means that maintenance is only carried out following a breakdown. This strategy may result in expensive repairs and prolonged downtime.

Predictive maintenance has been created as a proactive method of maintenance to solve this problem. In order to forecast when maintenance is required before a problem occurs, predictive maintenance uses sensors to gather data on a machine's performance. Manufacturers may decrease downtime, raise machine availability, and save maintenance costs by utilising predictive maintenance.

The Internet of Things (IoT), which offers real-time data collecting and processing capabilities, has been crucial in allowing predictive maintenance. IoT sensors may be used to gather a variety of data, including temperature, vibration, and power usage, which can then be analysed to find trends and anomalies that could point to a possible failure. With the use of this information, maintenance appointments may be made in advance of a breakdown, cutting downtime and increasing productivity.

The goal of this project is to create a predictive maintenance system utilising LoRa technology for an industrial robotic arm. A data analysis system that uses machine learning techniques to forecast when maintenance is required.Utilising LoRa technology will allow for real-time data collection and analysis, proactive maintenance planning, and a decrease in downtime and maintenance expenses.

CHAPTER 3

Literature Review

1.3 Background

In recent years, the use of predictive maintenance procedures for industrial machinery has grown in popularity due to its benefits over more conventional reactive maintenance methods. Utilising data analysis methods like machine learning algorithms, predictive maintenance works to forecast when a machine will likely need maintenance based on things like usage patterns and sensor data. Predictive maintenance can reduce downtime, save repair costs, and increase overall equipment efficiency by spotting possible maintenance issues before they arise.

Due to their capacity to rapidly and accurately complete repetitive tasks, robotic arms are widely utilised in a variety of industries, including manufacturing, logistics, and healthcare. Robotic arms need to be maintained on a regular basis, just like any other machine, to make sure they keep working properly. Robotic arms can benefit greatly from predictive maintenance methods since they can be used to spot possible problems before they cause downtime or equipment damage.LoRa (Long Range) technology is one possible method for integrating predictive maintenance for robotic arms. LoRa is a low-power wireless technology that works well for Internet of Things (IoT) applications because it can send data over great distances while consuming very little power.

Overall, using LoRa technology to implement predictive maintenance for robotic arms has the potential to increase the machines' dependability and effectiveness while lowering maintenance costs and downtime. But in order to fully take advantage of these advantages, it's critical to assess the body of literature on the subject and pinpoint the best implementation strategies. In order to accomplish that, this paper will present a thorough analysis of the state of the art in research on the use of LoRa technology to perform predictive maintenance for robotic arms.

3.2 Synthesis and Analysis

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. Here the authors of [3] talk 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 as well as the Internet of Industry and the Internet of Things (IoT). Their research assesses the noise robustness and LoRa efficiency for a specific industrial application.

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 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 Water Grid- Sense, a brand-new LoRa-based full- stack sensor node for IWSN.

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

Table 3.1: - Application Domains

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. 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 recognized by the authors here [12]: a small wireless communication range, inadequate or non-existent 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.

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 TSLoRa, 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 life cycle 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 problems of adopting predictive maintenance with IIoT technologies are also discussed, including data security and interoperability.

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

Table 3.2:- List of ML Algorithms Used

In this article [22], we'll talk about how the Internet of Things (IoT) can be used for industrial automation, with an emphasis on online monitoring and management. The authors 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. The research presented here [25] provides a method to improve the performance of LoRa networks in industrial settings. The authors use machine learning methods to analyse network data and optimise 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 proposed method is tested in a real industrial environment. The findings of this research have important implications for the deployment of LoRa networks in settings where reliable and effective communication is crucial. 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 program analyses 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.

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

Table 3.3: - Technology Stack and Limitations

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].

3.3 Gaps and Limitations

1. Limited range and coverage: LoRa technology has a limited range and coverage, which could lead to lost data and inaccurate forecasts if the sensors are unable to interact with the gateway in places with poor signal strength.
2. Limited bandwidth: Because LoRa technology has a constrained bandwidth, the volume of data that can be transmitted is also constrained. When trying to gather data from several sensors in a huge industrial environment, this can be a challenge.
3. Battery life: Because LoRa sensors often run on batteries, their lifespan may be shortened and they may need to be replaced frequently. In large industrial settings, this can be expensive and time-consuming.
4. Lack of standardisation: Because LoRa devices are not currently standardised, it may be challenging to integrate different sensors into a single system because they may use different protocols.
5. Data processing and analysis: Processing and analysing a lot of data are necessary for predictive maintenance utilising IIoT. Due to the overwhelming amount of data created by several sensors, which can be tricky to manage and analyse, this can be problematic.
6. Scalability: Managing and scaling LoRa technology can be challenging as industrial environments get bigger and the number of sensors needed for predictive maintenance rises.
7. Security: Security risks, such as hacking and data leaks, can affect LoRa technology. For industrial settings where sensitive data is gathered and stored, this can be a worry.

3.4 Data

3.4.1 Dataset-1 [AI4I 2020 Predictive Maintenance Dataset Data Set]

UDI	Product ID	Type	Air temperature [K]	Process temperature [K]	Rotational speed [rpm]	Torque [Nm]	Tool wear [min]	Machine failure	TWF	HDF	PWF	OSF	RNF
1	M14860	M	298.1	308.6	1551	42.8	0	0	0	0	0	0	0
2	L47181	L	298.2	308.7	1408	46.3	3	0	0	0	0	0	0
3	L47182	L	298.1	308.5	1498	49.4	5	0	0	0	0	0	0
4	L47183	L	298.2	308.6	1433	39.5	7	0	0	0	0	0	0
5	L47184	L	298.2	308.7	1408	40	9	0	0	0	0	0	0
6	M14865	M	298.1	308.6	1425	41.9	11	0	0	0	0	0	0
7	L47186	L	298.1	308.6	1558	42.4	14	0	0	0	0	0	0
8	L47187	L	298.1	308.6	1527	40.2	16	0	0	0	0	0	0
9	M14868	M	298.3	308.7	1667	28.6	18	0	0	0	0	0	0
10	M14869	M	298.5	309	1741	28	21	0	0	0	0	0	0
11	H29424	H	298.4	308.9	1782	23.9	24	0	0	0	0	0	0
12	H29425	H	298.6	309.1	1423	44.3	29	0	0	0	0	0	0
13	M14872	M	298.6	309.1	1339	51.1	34	0	0	0	0	0	0
14	M14873	M	298.6	309.2	1742	30	37	0	0	0	0	0	0
15	L47194	L	298.6	309.2	2035	19.6	40	0	0	0	0	0	0
16	L47195	L	298.6	309.2	1542	48.4	42	0	0	0	0	0	0
17	M14876	M	298.6	309.2	1311	46.6	44	0	0	0	0	0	0
18	M14877	M	298.7	309.2	1410	45.6	47	0	0	0	0	0	0
19	H29432	H	298.8	309.2	1306	54.5	50	0	0	0	0	0	0
20	M14879	M	298.9	309.3	1632	32.5	55	0	0	0	0	0	0
21	H29434	H	298.9	309.3	1375	42.7	58	0	0	0	0	0	0
22	L47201	L	298.8	309.3	1450	44.8	63	0	0	0	0	0	0
23	M14882	M	298.9	309.3	1581	30.7	65	0	0	0	0	0	0
24	L47203	L	299	309.4	1758	25.7	68	0	0	0	0	0	0
25	M14884	M	299	309.4	1561	37.3	70	0	0	0	0	0	0
26	L47205	L	299	309.5	1861	23.3	73	0	0	0	0	0	0

Figure 4.1: - AI4I 2020 Predictive Maintenance Dataset

The dataset consists of 10 000 data points stored as rows with 14 features in columns

UID: a unique identifier between 1 and 10,000

Product ID: made up of a variant-specific serial number and the letters L, M, or H for low (which represents 50% of all goods), medium (30%), and high (20%) product quality variants.

Air Temperature [K]: A random walk procedure was used ,which was then normalised to a standard variation of 2 K about 300 K.

Process temperature [K]: produced by adding the air temperature + 10 K to a random walk process with a standard variation of 1 K.

Calculated with a 2860 W power and a properly distributed noise, the rotational speed [rpm] Torque [Nm]: Torque numbers typically range from 40 to 10 Nm, with no negative values.

Tool Wear [min]: The quality variants H/M/L add 5/3/2 minutes of tool wear to the used tool in the process.

'machine failure' label that indicates, whether the machine has failed in this particular datapoint for any of the following failure modes are true

The machine failure consists of five independent failure modes **Tool Wear Failure (TWF):** In our dataset, this occurs 120 times. The tool will be changed or fail at a randomly chosen tool wear period between 200 and 240 minutes. At this point, the tool has been changed 69 times and has failed 51 times (assigned at random).

Heat Dissipation Failure (HDF): If the difference in temperature between the air and the process is less than 8.6 K and the tool's rotational speed is less than 1380 rpm, heat dissipation will result in a process failure. There are 115 data points that support this.

Power Failure (PWF): The power needed for the process is equal to the product of the torque and rotational speed (measured in rad/s). The method fails if this power is less than 3500 W or greater than 9000 W, which occurs 95 times in our dataset.

Overstrain Failure (OSF): The process fails owing to overstrain if the torque produced by tool wear and wear exceeds 11,000 minNm for the L product version (12,000 M, 13,000 H). For 98 datapoints, this is accurate.

Random Failures (RNF): Regardless of the process settings, every process has a 0,1% probability of failing. Only 5 datapoints in our dataset have this as their situation, which is fewer than the 10,000 datapoints that make up our dataset.

The process fails and the label "machine failure" is changed to 1 if at least one of the aforementioned failure scenarios is real. The failure mode that caused the procedure to fail is thus not transparent to the machine learning approach.

3.4.2 Dataset-2 [Microsoft Azure Predictive Maintenance]

This is an illustration of a data source that may be utilised to build predictive maintenance models. It includes the following information:

- Machine usage and conditions: A machine's operational circumstances, such as information gathered through sensors.
- Failure histories: The failure histories of a machine or a machine component.
- Maintenance history: The history of repairs made to a machine, such as error codes, prior maintenance tasks, or component replacements.
- Machine features: A machine's attributes, such as the location, manufacture, and model of the engine.

1	datetime	machineID	volt	rotate	pressure	vibration
2	1/1/2015 6:00	1	176.218	418.504	113.078	45.0877
3	1/1/2015 7:00	1	162.879	402.747	95.4605	43.414
4	1/1/2015 8:00	1	170.99	527.35	75.2379	34.1788
5	1/1/2015 9:00	1	162.463	346.149	109.249	41.1221
6	1/1/2015 10:00	1	157.61	435.377	111.887	25.9905
7	1/1/2015 11:00	1	172.505	430.323	95.927	35.655
8	1/1/2015 12:00	1	156.556	499.072	111.756	42.7539
9	1/1/2015 13:00	1	172.523	409.625	101.001	35.482
10	1/1/2015 14:00	1	175.325	398.649	110.624	45.4823
11	1/1/2015 15:00	1	169.218	460.851	104.848	39.9017
12	1/1/2015 16:00	1	167.061	382.484	103.781	42.6758
13	1/1/2015 17:00	1	160.264	448.084	96.481	38.5437
14	1/1/2015 18:00	1	153.353	490.673	86.0124	44.1086
15	1/1/2015 19:00	1	182.739	418.199	93.485	41.3672
16	1/1/2015 20:00	1	170.335	402.461	93.2358	39.7399
17	1/1/2015 21:00	1	182.467	501.919	85.7626	51.0215
18	1/1/2015 22:00	1	151.336	444.923	94.2474	42.1197
19	1/1/2015 23:00	1	172.535	511.886	91.3294	32.2488
20	1/2/2015 0:00	1	180.097	486.712	96.7339	38.8968
21	1/2/2015 1:00	1	169.606	519.453	78.8808	40.1569
22	1/2/2015 2:00	1	167.129	427.051	91.6999	44.6424
23	1/2/2015 3:00	1	158.271	422.811	92.4391	39.7819
24	1/2/2015 4:00	1	200.872	403.236	96.5355	32.5168
25	1/2/2015 5:00	1	181.258	495.778	93.4393	52.3559

Figure 4.2:- • Telemetry Time Series Data, Error, Each record in the failures file

- **Telemetry Time Series Data:** For the year 2015, 100 machines' hourly averages of voltage, rotation, pressure, and vibration were gathered.
- **Error:** These are errors that the machines encountered while they were in operation. These mistakes are not regarded as failures since they do not cause the computers to shut down. Since the telemetry data is gathered at an hourly rate, the error dates and times are rounded to the nearest hour.
- **Each record in the failures file** reflects the replacement of a component as a result of a failure. This information comes from the Maintenance data. Since the telemetry data is gathered at an hourly rate, this information is rounded to the nearest hour.

3.4.3 Dataset -3 [Ned 2 Niryo Robot]

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
5	200	0.8712871287	52	0
5	200	0.8712871287	52	0
5	200	0.8712871287	50	0
5	200	0.8712871287	45	0
5	200	0.8712871287	52	0
5	200	0.8712871287	53	0
5	200	0.8762376238	55	1
5	200	0.8762376238	61	1
5	200	0.8762376238	64	1
5	200	0.8762376238	61	1
5	200	0.8762376238	65	1
5	200	0.8762376238	63	1
5	200	0.8762376238	63	1
5	200	0.8762376238	59	1
5	200	0.8712871287	53	0
5	200	0.8762376238	59	1
5	200	0.8762376238	56	1

Figure 4.3:- Ned 2 Niryo Dataset

No_of_Position: This column appears to indicate how many positions are associated with a certain process or system element.

Speed: The speed connected to the observed data points is probably represented by this column.

Seconds: It looks like this column is a measurement of time; it may be the amount of time in seconds that a certain procedure or event takes.

Temperature: The temperature recorded at the specified "No_of_Position," "Speed," and "Seconds" combination is shown in this column.

Target: Binary values (0 or 1) are present in this column with the label "Target

CHAPTER 4

SYSTEM REQUIREMENTS SPECIFICATION

4.1 Introduction

4.1.1 Purpose

Utilizing data analysis and machine learning algorithms to forecast when maintenance is necessary in order to avoid equipment failure or downtime is known as predictive maintenance. Due to the massive amount of data produced by connected machines and devices, this practice is made even more crucial in an IIoT (Industrial Internet of Things) environment.A wireless communication technology called LoRa (great Range) is frequently utilized in IIoT applications because it can send data over great distances with little battery usage. LoRa can be used to transfer sensor data from equipment to a central system for analysis when utilized for predictive maintenance.

Predictive maintenance is used in an IIoT setting employing LoRa to increase equipment efficiency and dependability, decrease downtime, and cut maintenance costs. repair teams can prevent equipment failure and unplanned downtime by using sensor data to predict when repair is necessary. This reduces the requirement for reactive maintenance and lowers the likelihood of unplanned downtime. Increased productivity and considerable cost reductions can result from this.

4.1.2 Intended Audience and Reading Suggestions

The primary target audience for a topic on "predictive maintenance in IIoT environment using LoRa" would be experts and researchers in industrial automation, the Internet of Things (IoT), and wireless communication technologies. Those who work in the manufacturing, transportation,energy, and utility industries, where preventative maintenance can help maximize the operational efficiency of machines and equipment, would find this topic to be of special interest.Academic research articles on IoT, wireless communication technologies, and predictive maintenance could be some suggested readings for this subject. Additionally, industry leaders like IoT solution providers, automation firms, and wireless communication vendors may publish articles and whitepapers that offer insights into the most recent advancements and trends in the sector.

4.1.3 Project Scope

A system that can anticipate future equipment failures in industrial machinery and alert maintenance staff before any breakdowns occur is part of the predictive maintenance project scope for the Industrial Internet of Things (IIoT) environment. Real-time data from the machines will be collected by the system using sensors, and it will then wirelessly send that data using LoRa technology to a cloud-based platform for analysis.

The following elements will be included in the project:

1. Data transmission: The gathered data will be wirelessly transmitted to a cloud-based platform using LoRa technology.
2. Machine learning techniques will be used to analyze the sensor data in real-time in order to spot probable equipment breakdowns.
3. Notifications for maintenance: A dashboard or mobile application will alert maintenance staff of probable equipment faults.

The solution will assist increase machine availability, boost productivity, and lower maintenance expenses for equipment. Furthermore, LoRa technology enables long-range wireless communication, making it appropriate for expansive industrial settings.

4.2 Overall Description

4.2.1 Product Perspective

In order to provide a full solution, the product viewpoint of predictive maintenance in an IIoT context employing LoRa entails the integration of multiple hardware and software components.The hardware consists of sensors, gateways for the LoRa (Low Power Wide Area Network), devices for processing and analyzing data, and devices for transmitting data to machines and equipment. The sensors can be fastened to various machine and equipment parts to collect information on variables including temperature, pressure, vibration, and humidity. The data is transmitted to the cloud, where it is stored and analyzed, via the LoRa gateways.

The system's software consists of machine learning algorithms, data analytics software, and visualization software. The data gathered from the sensors is analyzed by machine learning algorithms to look for trends, identify anomalies, and predict probable problems. While the visualization tools are used to present the insights in an approachable manner, the data analytics tools are used to process the data and extract meaningful insights.

The IIoT predictive maintenance solution using LoRa is created to be adaptable and scalable, allowing it to be implemented in a variety of industrial settings. It is also made to be user-friendly, with a straightforward interface that makes it easy for users to access and analyze data.

4.2.2 Product Features

The following product benefits can be offered by predictive maintenance in an IIoT setting employing LoRa (Long Range) technology:

1. Remote monitoring: The long-range, low-power communication capabilities of LoRa technology enable remote monitoring of equipment performance and condition. This aids in seeing possible problems and fixing them before they result in prolonged downtime or failure.
2. Real-time analytics: By gathering information from sensors on the equipment, the system may do in-the-moment data analysis and offer insights into the functionality and state of the machinery. This makes it easier to foresee possible failures and take proactive corrective action.
3. Predictive maintenance planning: The system can produce maintenance schedules that optimise maintenance activities and reduce downtime based on the data gathered and analysed.
4. Cost-effective: Compared to more expensive alternatives like wired networks, LoRa technology is inexpensive, giving it an affordable solution for predictive maintenance.
5. Scalability: The LoRa technology-based IIoT ecosystem is scalable, enabling the addition of new hardware and sensors without having an impact on the current infrastructure.

6. Reduced maintenance expenses: By spotting flaws before they develop into serious difficulties, predictive maintenance using IIoT and LoRa technologies can help decrease maintenance costs by avoiding the need for pricey repairs or replacements.

7. Improved safety: By identifying possible safety risks, predictive maintenance enables the remedial action to be performed to stop accidents or injuries.

4.2.3 User Classes and Characteristics

Users of predictive maintenance solutions in an IIoT setting employing LoRa may have the following characteristics:

1. Users of predictive maintenance systems must possess a particular level of technical skill in order to comprehend and use the system properly.
2. Analytical abilities: In order to evaluate the data produced by the system and base decisions on that data, users of predictive maintenance systems must possess strong analytical abilities.
3. Time management abilities: In order to priorities maintenance jobs according to their urgency, maintenance specialists, in particular, need to have strong time management abilities.
4. Collaborative skills: Users of predictive maintenance systems must have strong collaborative abilities in order to effectively interact with other maintenance team members.

4.2.4 Operating Environment

The Industrial Internet of Things (IIoT) environment, where LoRa (Long Range) is used for predictive maintenance, is dynamic and complicated. The following elements make up this system's operational environment:

1. IIoT Devices: In an industrial context, these are the physical assets that produce data and need upkeep. Machines, sensors, and actuators are a few examples.
2. Infrastructural support for communication between IIoT devices and the cloud platform is provided via the LoRa network. Its long-range communication capabilities and low power consumption make it appropriate for use in industrial environments.
3. Cloud Platform: The IIoT devices' primary data storage location is the cloud platform. The data is analysed to reveal information about the equipment's condition and forecast maintenance needs.
4. Analytics and machine learning: Algorithms for analytics and machine learning are used to analyse data produced by IIoT devices and find trends that point to the need for maintenance.

4.2.5 Design and Implementation Constraints

Design Constraints are listed below:

1. Data compatibility
2. Data availability

4.3 External Interface Requirements

4.3.1 User Interfaces

1. Software for data acquisition and processing: This part is in charge of gathering data from sensors and analyzing it to spot anomalies and forecast maintenance needs.
2. Software for user authentication and authorization: This element is in charge of looking after user accounts.
3. Dashboard software: This part is in charge of providing a user-friendly display of the data gathered by the data gathering and processing software, such as graphs, charts, and other visualizations.
4. Software for alert management: This part is in charge of producing alerts depending on the information gathered and processed by the system.

4.3.2 Hardware Interfaces

1. Niryo Ned 2 (ROS Integration): Within the framework of its Robotic Operating System (ROS), Niryo Ned 2 generates sensor data.ESP8266 is one of the external devices to which ROS transmits sensor data using the ROS message format.
2. ESP8266 WiFi Module: ESP8266 serves as a bridge between the Arduino Uno and the Niryo Ned 2.uses WiFi connectivity to receive sensor data from Niryo Ned 2 over ROS.sends the obtained data via serial communication to the Arduino Uno.
3. Arduino Uno: The Arduino Uno is a microcontroller that connects to the LoRa Gateway and ESP8266.obtains sensor data through serial communication from the ESP8266.gathers and, if required, preprocesses the data.uses the LoRa protocol to send the processed data to the LoRa Gateway.
4. LoRa Gateway:Functions as a central hub for collecting data from multiple LoRa sensors and devices, including the Arduino Uno.Utilizes LoRa communication to receive data from Arduino Uno.Aggregates data from various sources and prepares it for transmission

to the LoRa Network Server.

4.3.3 Software Interfaces

1. LoRaWAN Gateway: The LoRaWAN gateway is in charge of receiving data from sensors and transmitting it to the cloud server. The LoRaWAN gateway software should be connected with the predictive maintenance system.
2. The LoRaWAN gateway sends data to the cloud server, which collects and processes it. To interface with the server and receive data, the predictive maintenance system should be coupled with cloud server software.
3. Data Storage: To store the incoming data, the predictive maintenance system needs to be coupled with a certain version of the database software.
4. Data Analytics and Visualization: To perform predictive analysis and visualization of data, the predictive maintenance system may be linked with specific data analytics and visualization software.

4.3.4 Communications Interfaces

1. LoRa Communication Protocol: The system must use the LoRa communication protocol to enable communication between connected devices.
2. Data Transfer Rates: The system must have a high data transfer rate to enable the transmission of real-time data to the central system.
3. Security and Encryption: The system must implement appropriate security measures to ensure that data transmitted over the network is secure. This may include data encryption during transmission.
4. Web Browser Interface: The system should provide a web browser interface for users to access and manage the system remotely.

4.4 Other Nonfunctional Requirements

4.4.1 Performance Requirements

1. Latency: The predictive maintenance system should have low latency, which means it should take as little time as possible to transmit data from sensors to the system and receive insights from the system.
2. Reliability: The system should be dependable and provide accurate predictions of probable machine or equipment breakdowns.
3. Range: A fundamental aspect of LoRa technology is the ability of LoRa sensors to communicate across great distances.

4.4.2 Safety Requirements

1. Electrical safety: To prevent electrical risks such as electric shock, short circuits, and electrostatic discharge, the predictive maintenance system must be developed and installed in accordance with appropriate electrical safety regulations.
2. Radiofrequency safety: LoRa technology runs at radiofrequencies that may interfere with other wireless devices, causing harm to persons and equipment. As a result, the system must adhere to appropriate radiofrequency safety regulations in order to avoid radio frequency interference and limit radiofrequency exposure.

4.4.3 Security Requirements

1. Authentication: It is critical to authenticate both devices and users who connect to the IIoT network. This can be accomplished by employing secure credentials such as passwords, digital certificates, or biometrics.
2. Access control: It must be implemented to ensure that only authorised devices and users have access to the IIoT network and its resources. This can be accomplished by utilising role-based access control and other access management strategies.
3. Encryption: To prevent eavesdropping and tampering, all data transmitted across the IIoT network should be encrypted using safe cryptographic algorithms.
4. Data integrity: Data integrity must be maintained throughout the IIoT system's lifecycle. This involves safeguarding against data corruption, unauthorised changes, and other forms of assault.

CHAPTER 5

HIGH LEVEL DESIGN

5.1 Introduction

By utilising data analysis and machine learning techniques to forecast when maintenance is required, predictive maintenance is a proactive maintenance strategy that tries to identify probable equipment faults before they happen. Lora (Long Range), a wireless communication technology that permits long-range, low-power communication between devices, is one tool that may be utilised for preventative maintenance.

Real-time data from sensors on equipment, such as those measuring temperature, vibration, and pressure, may be collected using Lora. This data can then be analysed to look for trends and anomalies that could point to potential breakdowns. In order to save downtime, lower maintenance costs, and enhance equipment dependability, maintenance teams may use predictive maintenance with Lora to proactively solve problems before they become serious.

Companies must set up a network of Lora sensors and gateways that can communicate data to a centralized data management system in order to execute predictive maintenance using Lora. The data may then be analysed by this system using machine learning techniques to provide information on the operation and upkeep requirements of the equipment. For companies that depend on reliable equipment, predictive maintenance utilising Lora has the potential to revolutionize maintenance procedures and result in considerable cost savings.

5.2 Design Considerations

5.2.1 Design Goals

The design approach followed is data-driven approach.It involves collecting data from equipment(Ned Niryo 2 Robot), processing and analyzing it using machine learning algorithms to predict when maintenance or repairs will be required.

5.2.2 Architecture Choices

1. Pub/Sub Model
2. Client/Server Model

5.3 High Level System Design

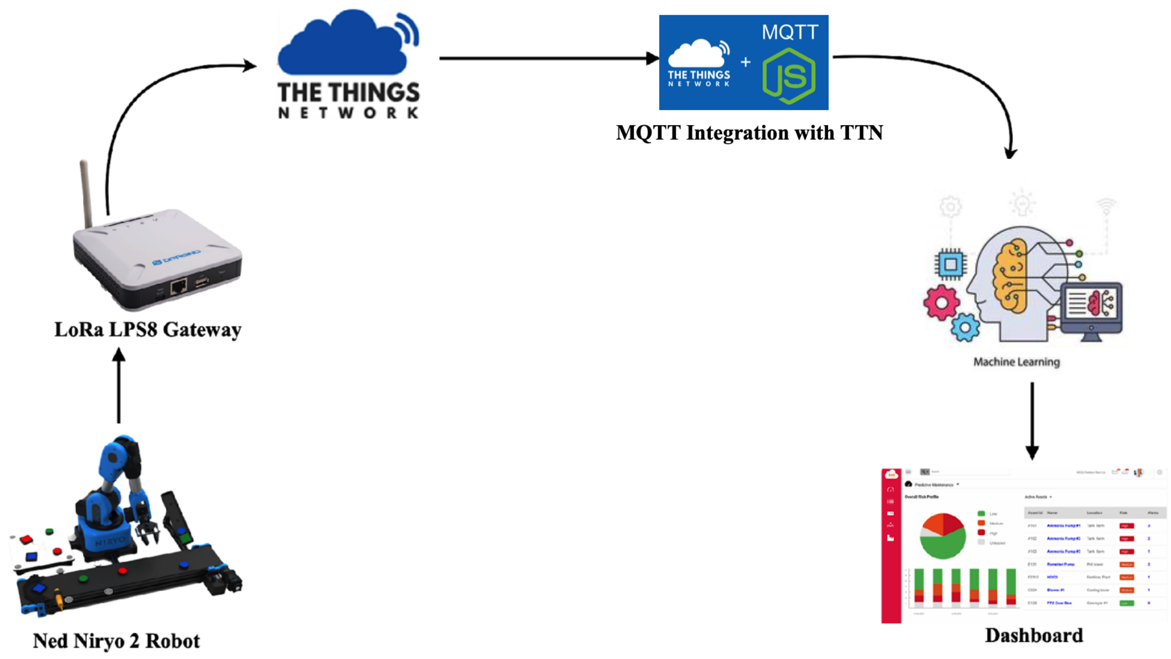


Figure 5.1: - Architecture Diagram

Ned2 is a 6-axis collaborative robot arm.

LPS8 is an open source LoRaWAN Gateway, which lets you bridge a LoRa wireless network to an IP network via WiFi or Ethernet.

The Things Network provides an open LoRaWAN network with a set of open tools to build and Iot Application.

The Things Stack exposes an **MQTT server t**o work with streaming events.

Machine learning model is an algorithm that can make predictions on unseen datasets.

5.4 Use Case Diagram

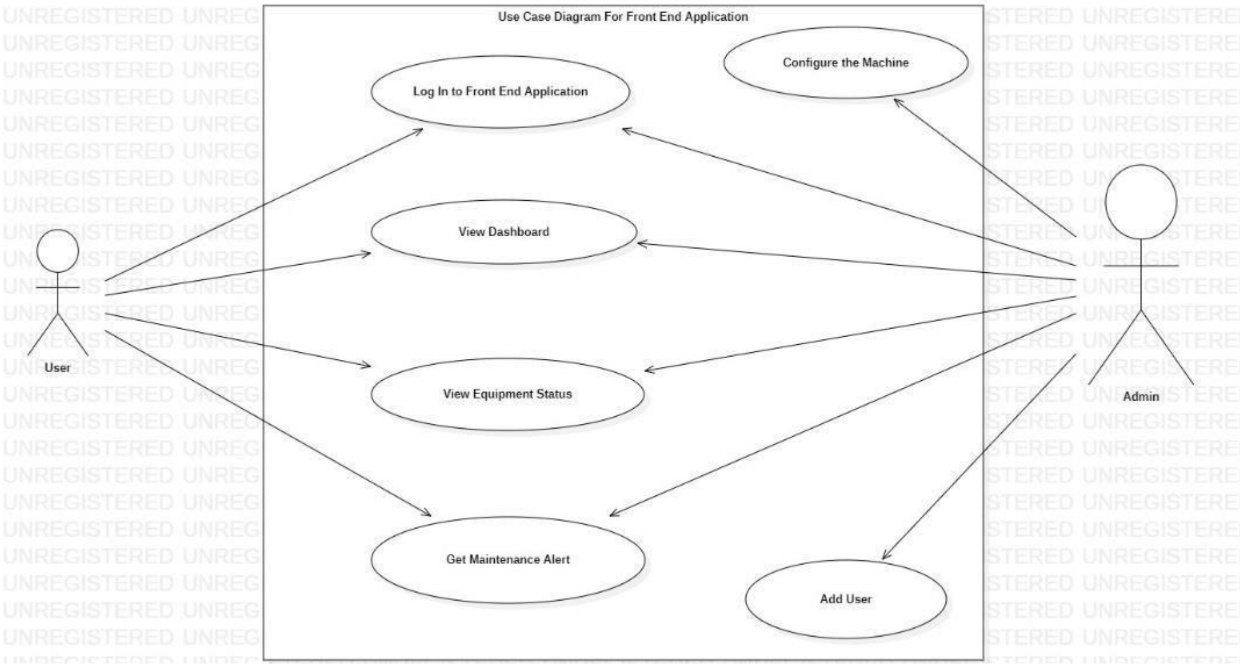


Figure 5.2: - Use Case Diagram

5.5 External Interfaces

- **LoRaWAN Interface:**

Purpose: Promotes communication between the LoRaWAN network and edge devices (ESPs, Arduinos, etc.).

Specifications:

- outlines the protocol for long-distance data transmission.
- describes the process by which devices join and authenticate with the LoRaWAN network.

- **MQTT Interface:**

Purpose: allows for communication between the gateway or central server and edge devices.

Specifications:

- Specifies MQTT topics for sensor data publication and subscription.
- Describes the MQTT message format that is used for communication between devices and the central server.

- **The Things Network (TTN) Interface:**

Purpose: acts as a bridge between edge devices and the backend.

Specifications:

- Describes how data transmission and storage can be integrated with TTN.
- Specifies the authentication procedures and TTN API endpoints.

- **Machine Learning Model (SVM) Interface:**

Purpose: combines the Support Vector Machine (SVM) with data analysis and forecasting.

Specifications:

- explains the format that the SVM model expects for input data.
- specifies the forecasts' or classifications' output format.

- **Dashboard Interface (Django, JavaScript, HTML):**

Purpose: Provides a user interface for data visualization and interaction.

Specifications:

- describes the Django API endpoints that can be used to get processed data back.
- explains how the JavaScript and HTML elements behave and are organised.

- **ROS (Robot Operating System) Topics Interface:**

Purpose: promotes communication amongst the various robotic system components (Niryo).

Specifications:

- Defines ROS topics for exchanging messages between robotic components.
- Specifies the data format and frequency of communication.

- **Documentation Interface:**

Purpose: Provides comprehensive documentation for developers and users.

Specifications:

- Includes API documentation for MQTT, TTN, Django, and ROS interfaces.
- Provides guides on setup, configuration, and troubleshooting.

- **Data Flow and Integration Interface:**

Purpose: Illustrates the flow of data and integration points between different components.

Specifications:

- diagrams showing how data is transferred from edge devices to the dashboard.
- explains the steps involved in processing, SVM model analysis, and dashboard presentation of data.

- **Versioning Interface:**

Purpose: Allows for updates and changes without disrupting existing integrations.

Specifications:

- explains version control methods for API endpoints, MQTT topics, and other interfaces.
- describes the protocol used to transmit version information between requests and answers

CHAPTER 6

SYSTEM DESIGN

6.1 Design Details

6.1.1 Novelty

A relatively new notion, the use of LoRa technology for IIOT predictive maintenance relies on the technology's capacity to offer low-power, long-range connectivity for IoT devices, which makes it excellent for industrial applications.

6.1.2 Innovativeness

Because it enables real-time monitoring and analysis of equipment health, which can help identify and prevent potential failures before they happen, the use of predictive maintenance in IIOT using LoRa is novel.

6.1.3 Interoperability

The predictive maintenance system has to be able to communicate with various IIOT hardware and software platforms as well as various LoRa networks in order to be interoperable.

6.1.4 Performance

The predictive maintenance programme should be created to provide high-performance, real-time equipment health monitoring. To allow prompt intervention prior to equipment breakdown, the system should be able to deliver accurate and rapid data analysis.

6.1.5 Security

To avoid unauthorised access and safeguard confidential information, the predictive maintenance system should be created with security in mind. In order to safeguard data integrity and confidentiality and to avoid data breaches, the system should employ secure communication methods.

6.1.1 Reliability

The predictive maintenance system needs to be dependable and offer ongoing equipment health monitoring. Any potential failures should be detected by the system and reported to the maintenance team.

6.1.2 Maintainability

It should be simple to maintain and fix the predictive maintenance system. Modular components should be included in the system's design to make it simple to swap out any broken elements.

6.1.3 Portability

The predictive maintenance system must be transportable and simple to set up in various IIOT settings. The system should be able to operate with various networks and communication protocols.

6.1.4 Legacy to modernization

The LoRa technology should enable the predictive maintenance system to interface with current legacy systems and modernise them.

6.1.5 Reusability

The predictive maintenance system needs to be created with reusability and scalability in mind. The system should be able to handle various IIOT platforms and devices, making it simple to deploy in various settings.

6.1.6 Application compatibility

The IIOT platforms should be simple to interface with since the predictive maintenance system should work with a variety of applications.

6.1.7 Resource utilization

In order to enable real-time monitoring and analysis of equipment health, the predictive maintenance system should be built to optimize resource utilization, minimizing the consumption of power and bandwidth.

6.2 IoT Architecture

An IoT system's layers and components are described in detail by the Internet of Things (IoT) architecture. It offers a methodical approach for creating interoperable, scalable, and flexible Internet of Things systems.

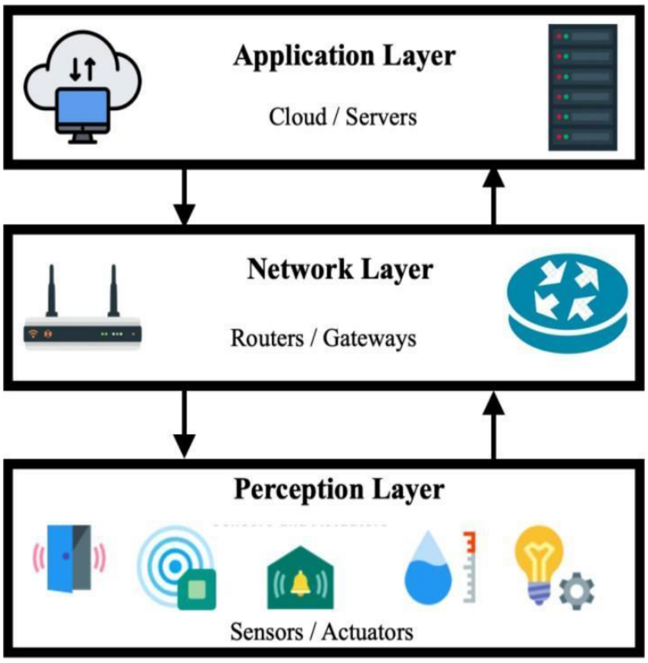


Figure 6.1: - A Generic Three Layered IoT Architecture

The above components are typically organized into three layers:

1. The perception layer, which includes the devices and sensors that collect data from the environment.
2. The network layer, which includes the connectivity layer and the cloud platform that facilitates the transfer and storage of data.
3. The application layer, which includes the analytics and applications that make use of the data generated by IoT devices.

6.3 LoRa Architecture

A low-power wide-area network (LPWAN) technology called LoRa (Long Range) is utilised for long-distance communication between IoT devices. The LoRa architecture is made up of a number of parts that work together to support low-power, long-range wireless communication. The following are the main elements of LoRa architecture:

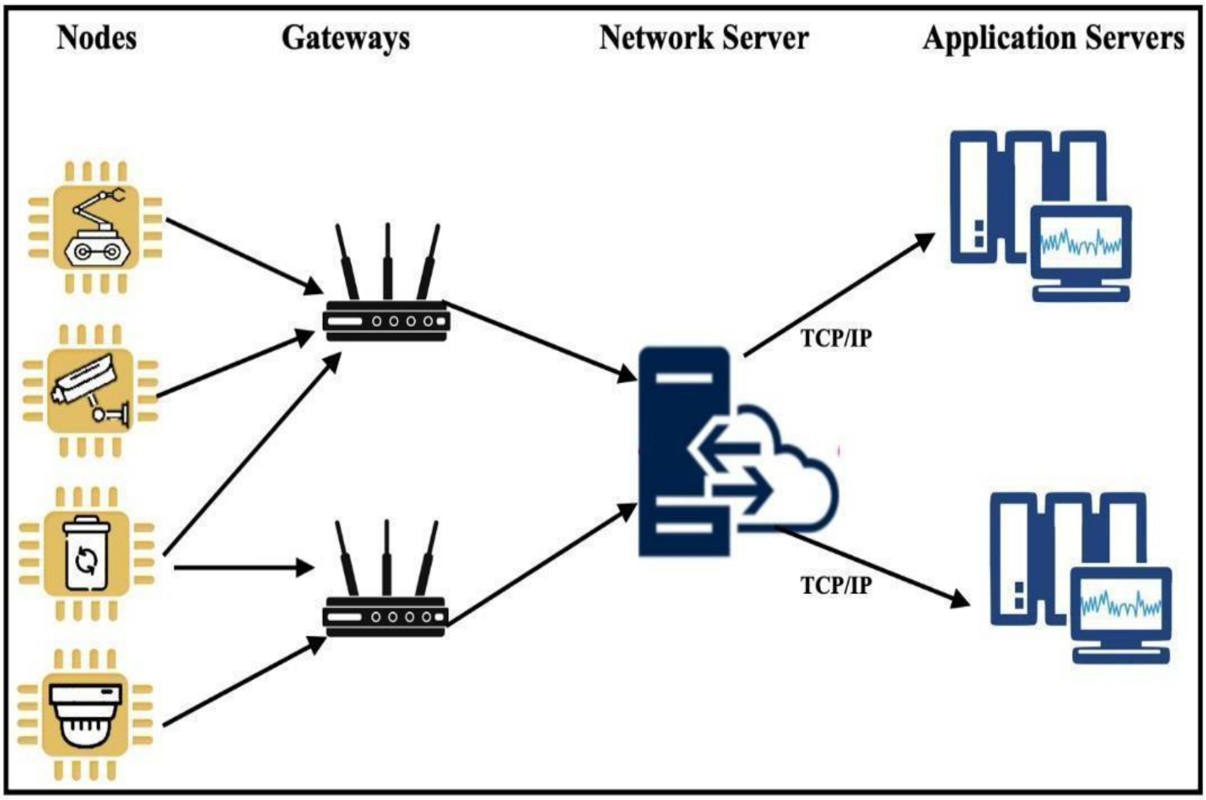


Figure 6.2: - A Generic LoRa Architecture

1. End Devices: These are the Internet of Things (IoT) gadgets that use LoRa technology to deliver and receive data. They are often battery-powered and made to use little electricity.
2. Gateways: Data from end devices is forwarded to the network server through LoRa gateways. They are in charge of translating the LoRa radio signal into internet-transmittable IP packets.
3. Network Server: The network server controls the flow of information between applications and endpoints. It receives data from gateways and routes it to the appropriate application server

CHAPTER 7

METHODOLOGIES

7.1 Robot Design

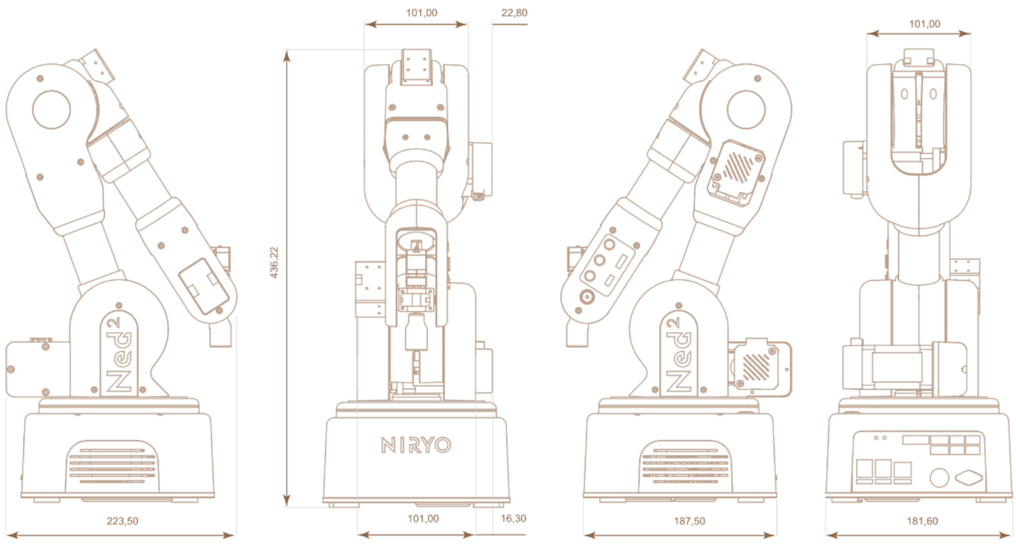


Figure 7.1: -Structure of Robot

Ned2, an open-source collaborative robot with six axes of motion, was created. It is meant for research, teaching, and Industry 4.0. Ned's replacement, Ned2, is more reliable and contains several enhancements that, when combined with an enhanced human-machine interface, enable users to learn collaborative robotics even more.

The rear panel of the Ned 2 is open and easily accessible, making it headache-free to attach your sensors and accessories.

Figure 7.2: -Back Panel

7.2 Pub/Sub Model

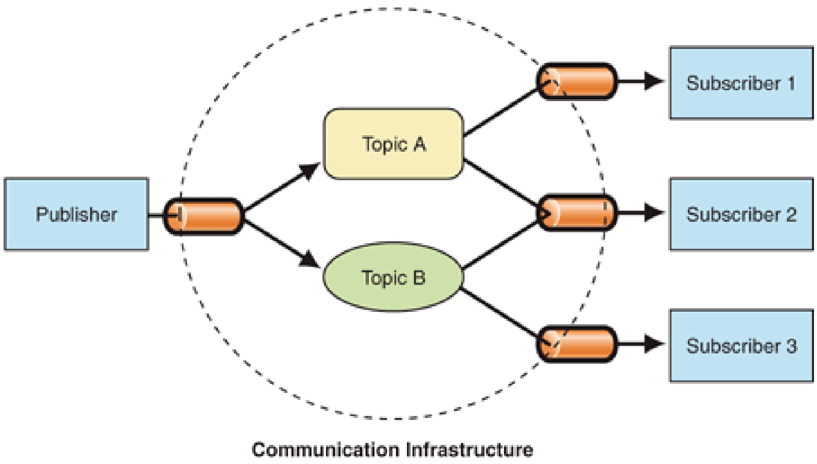


Figure 7.3: - Pub Sub Model

In order to enable publishers to send messages to a central hub (broker) and subscribers to receive particular messages of interest, the publish-subscribe (pub-sub) model is used to facilitate communication between components.

7.3 Client/Server Model

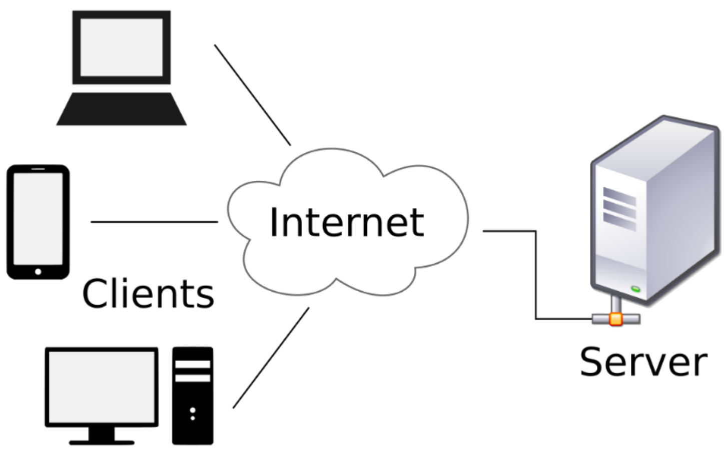


Figure 7.4: - Client/Server Model

In a client-server computing architecture, client devices send requests for resources or services, and servers respond by sending the required information or functionality.

CHAPTER 8

IMPLEMENTATION AND PSEUDOCODE

8.1 Pseudocode for Implementing SVM ML Model

```
# 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 8.1:- Pseudocode for SVM

- 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.

- To sum up, we used your training data to train an SVM model with the RBF kernel, obtained good accuracy, and assessed the model's performance on both the training and test sets. The classification report and confusion matrix offer more information about the model's effectiveness for each class. The balance between the classes in your dataset can be understood through the class distribution analysis.

8.2 Connectivity to LoRa

Figure 8.2: -LoRa Wifi

A LoRaWAN gateway is a piece of hardware that accepts LoRa signals from other LoRa devices and transforms them into internet protocol (IP) packets that may be transmitted online. Additionally, the gateway obtains IP packets from the internet and transforms them into LoRa signals that can be transmitted to LoRa devices.

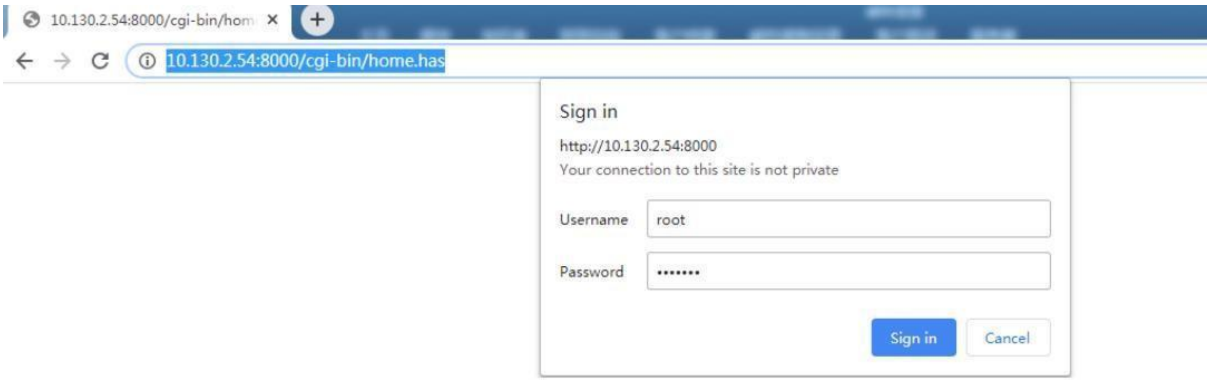


Figure 8.3: -Login Interface of LPS8

1. Your device must be connected to the LPS8 WiFi network.

2. Enter the IP address of the LPS8 Wifi device into the address bar of your web browser when it has opened. This is often stated in the device's user manual or can be discovered by searching the network for linked devices.

3. Press Enter to access the login screen after entering the IP address.

4. Enter your username and password, which are often included in the user handbook or are editable by the user

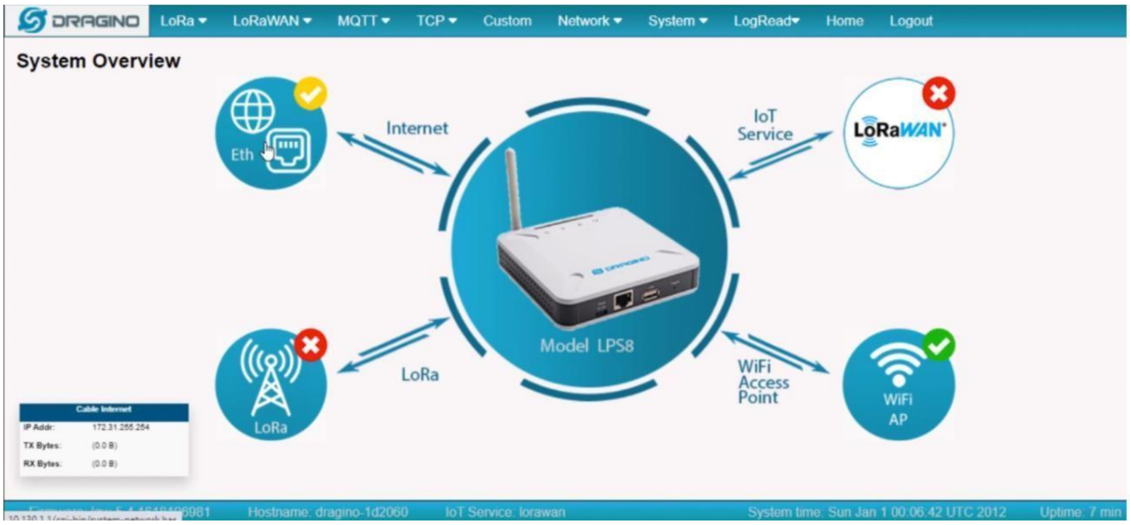


Figure 8.4: -LPS8 home page

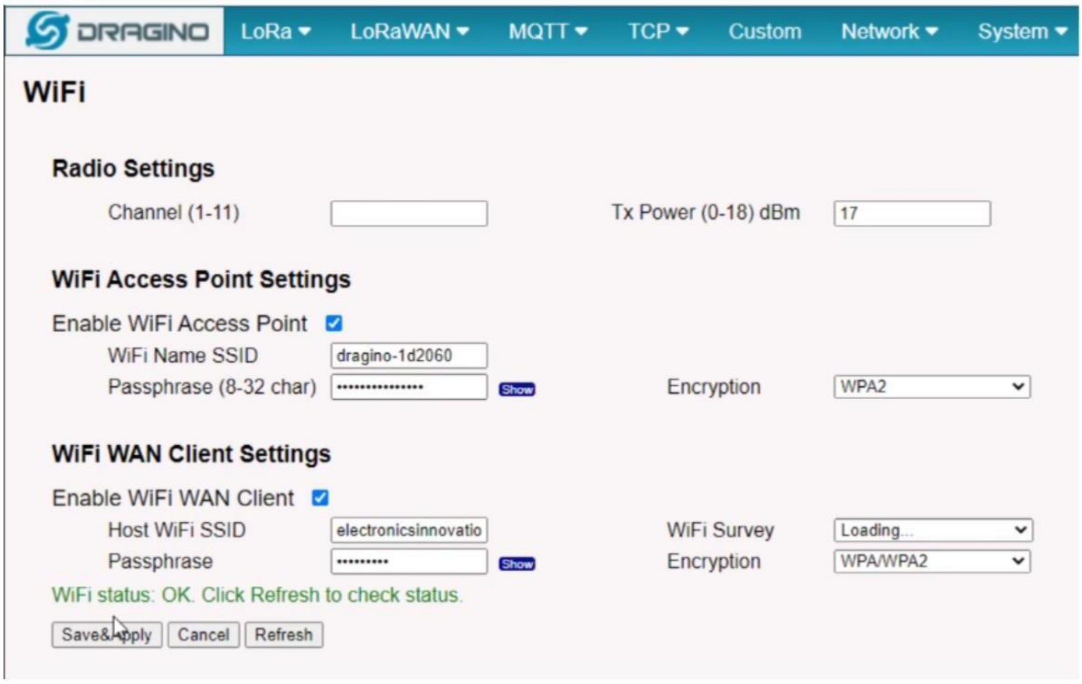


Figure 8.5: - LoRaWAN Page

1. Find the WiFi WAN Client settings: You may find them in the section for network or connectivity settings. The WiFi network credentials should be entered: The network name (SSID) and password will be included. Choose the security protocol, which must be the same as the WiFi network's security protocol.

2. Selecting an IP address configuration Either DHCP or a static IP address can be chosen for this. The most common user-recommended setting is DHCP.

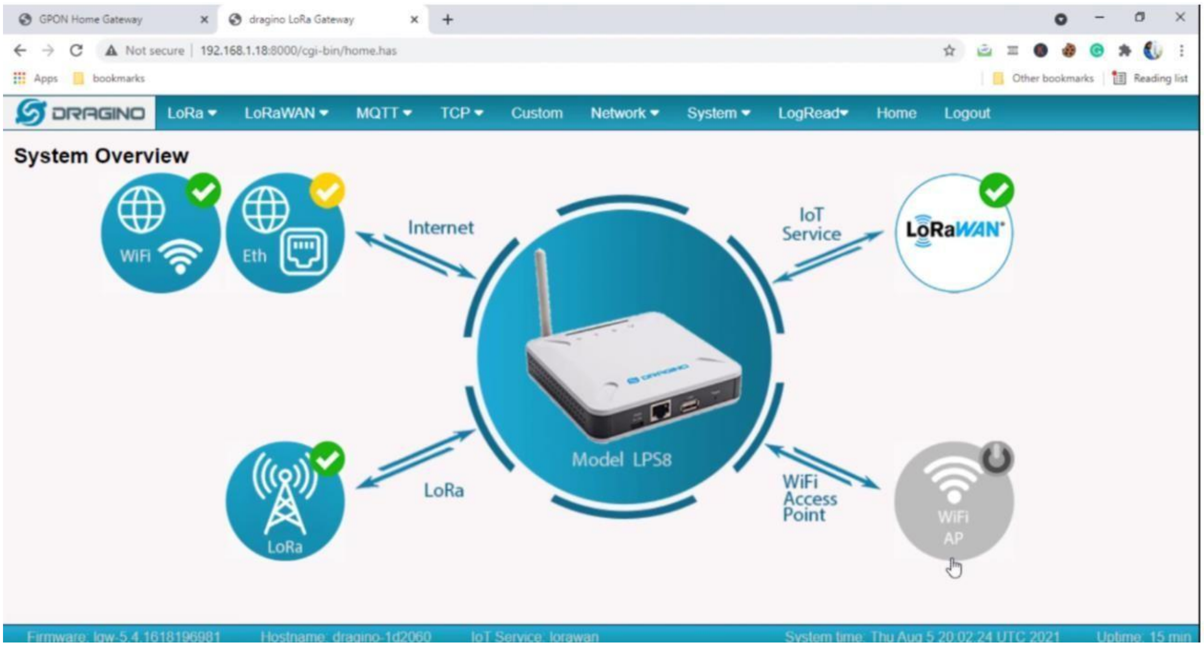


Figure 8.6: **-Gateway successfully connected to the router**

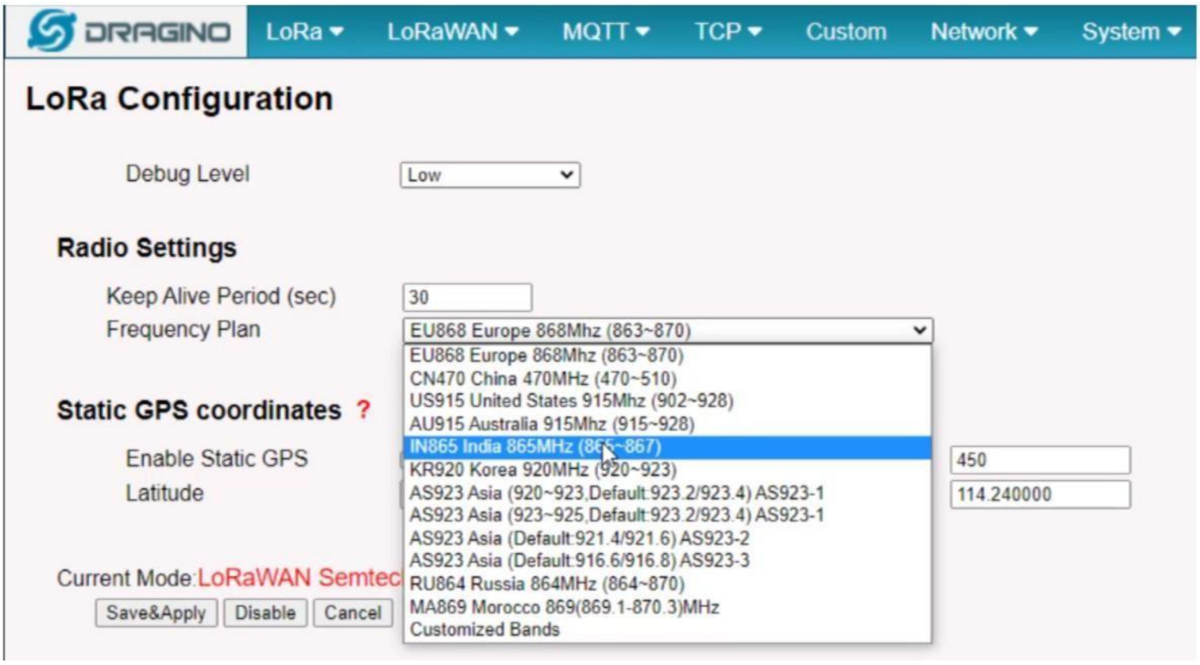


Figure 8.7 : -*Configure the Lora frequency. So we choose the IN865-867 band is*

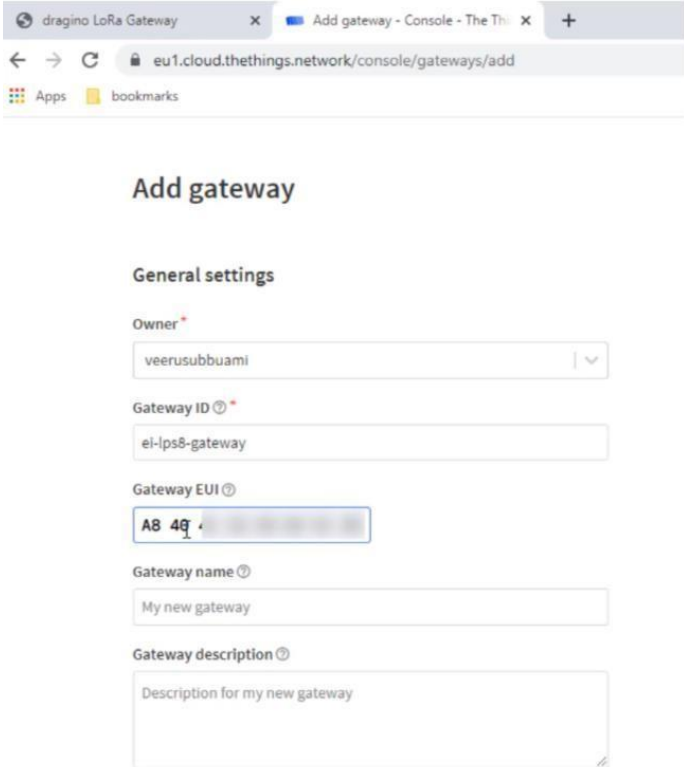


Figure 8.8: **-Gateway Registration Page**

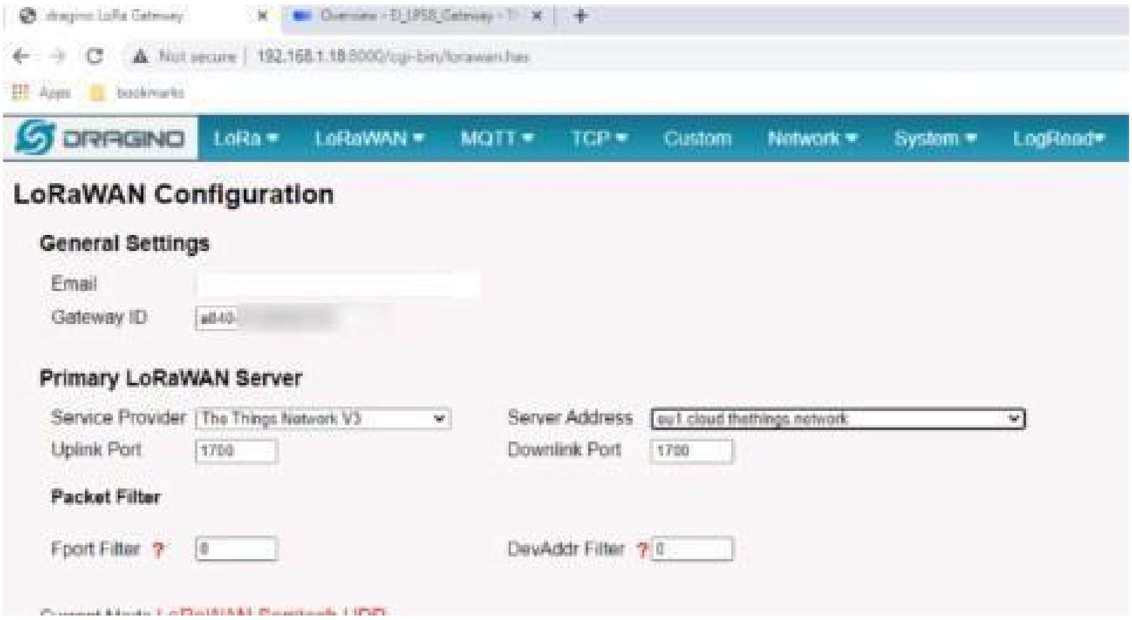


Figure 8.9: -*Gateway Management Page,service provider is "The Things network V3" and the server address is "eu1.cloud.thethings.network"*

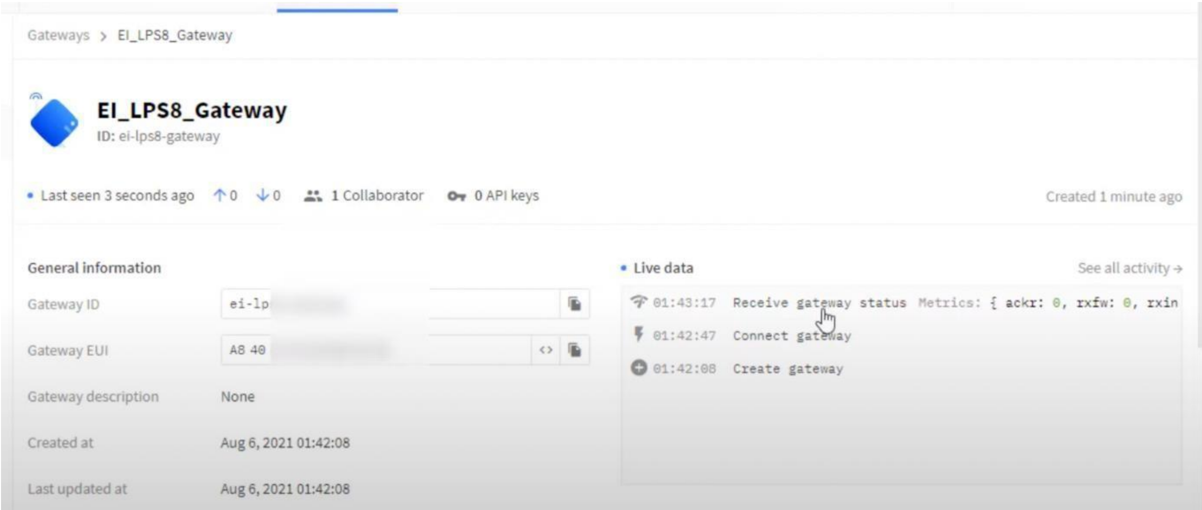


Figure 8.10: **-Things Network Page with Gateway Status**

You may try sending some test data from a LoRa device and checking if it is received by the gateway to ensure that everything is operating as it should. To discover whether there are any faults or problems that need to be fixed, you may also examine the gateway logs or online interface.

CHAPTER 9

RESULTS & DISCUSSION

```
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 9.1:- **Confusion Matrix**

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

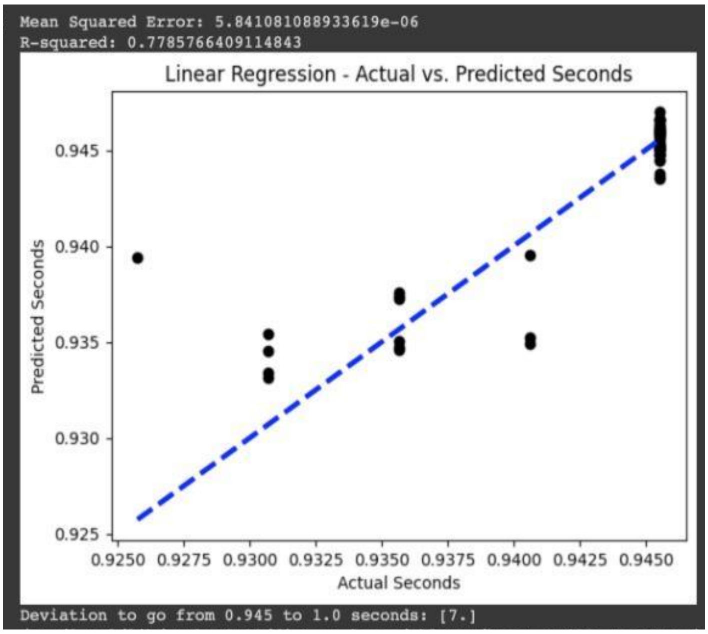


Figure 9.2:- **Linear Regression Graph**

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.

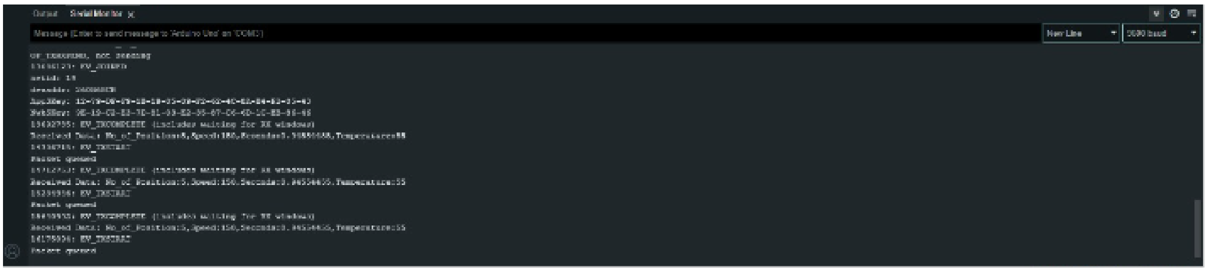


Figure 9.3: - Sending Data to LoRa Gateway

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.

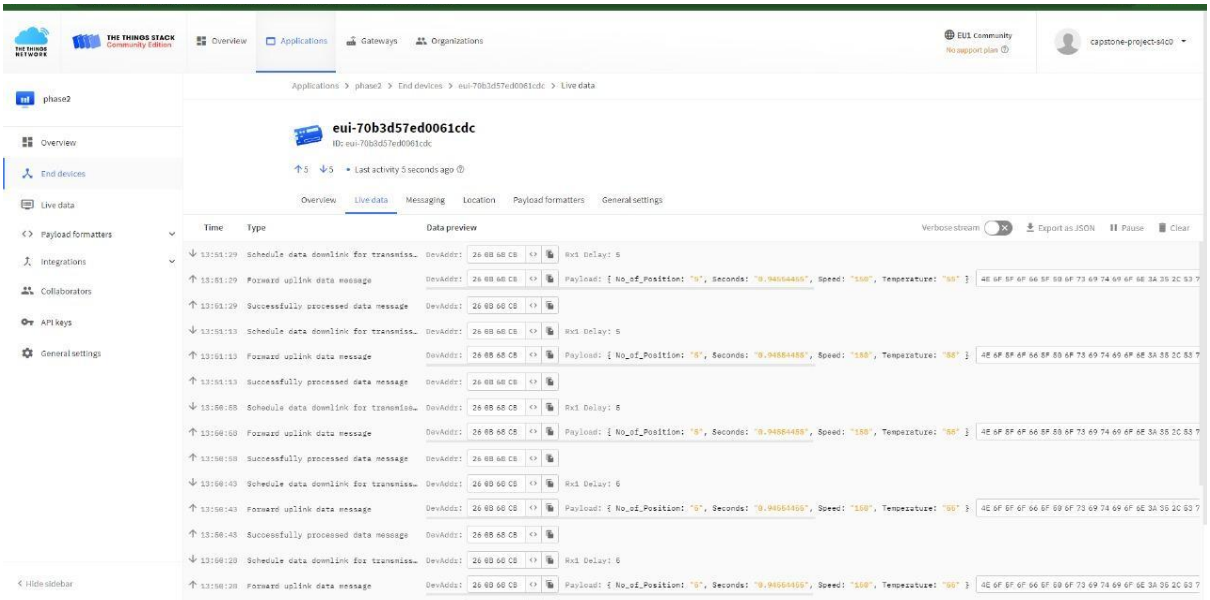
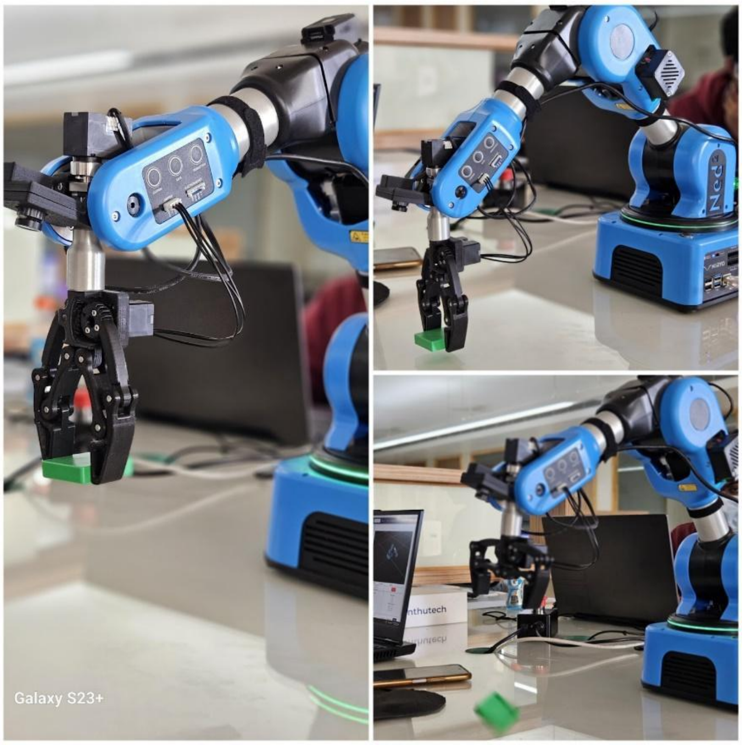


Figure 9.4: -Data Received on TTN

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.



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 9.5: -Pick, Intermediate and Place Positions

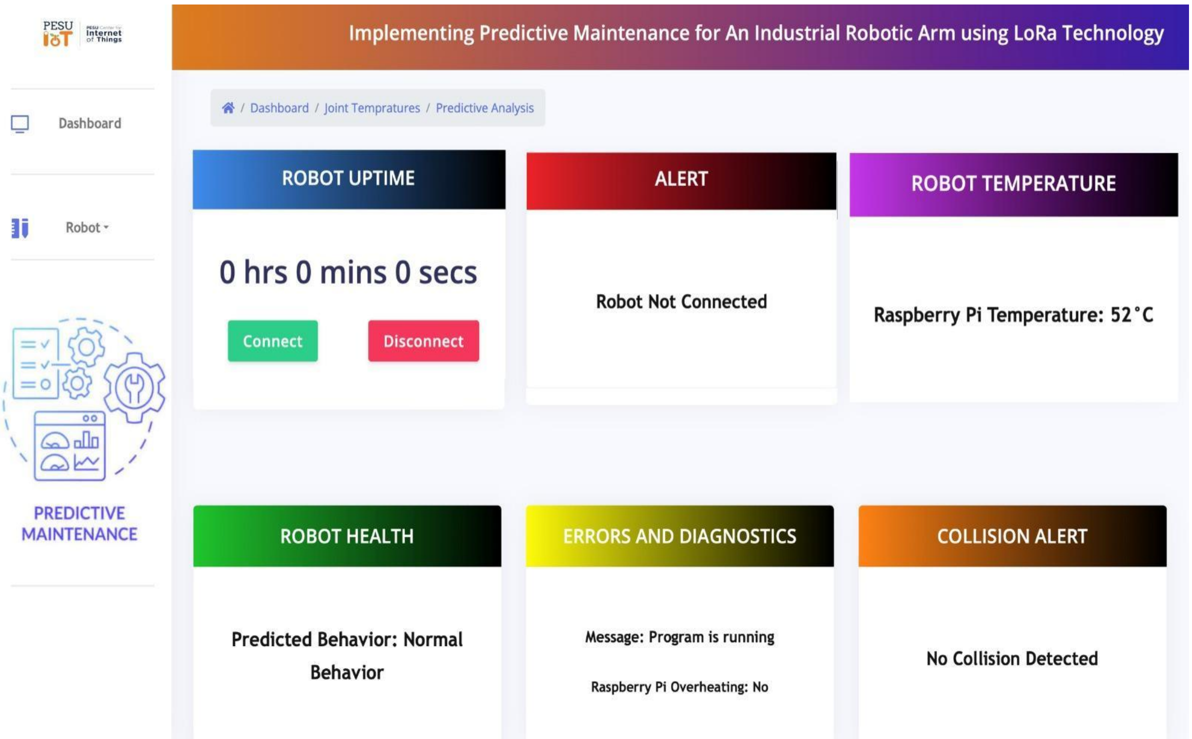


Figure 9.6: - Dashboard

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

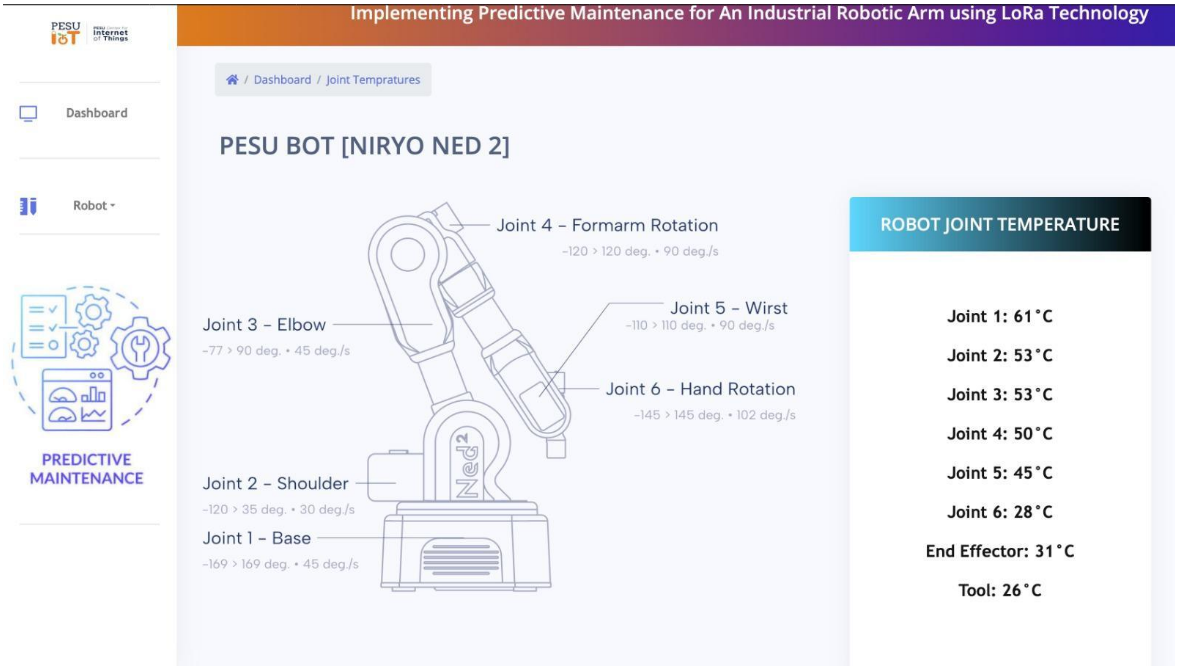


Figure 9.7: - Joint Temperature

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.

CHAPTER 9

CONCLUSION AND FUTURE WORK

The objective of the project was to develop a system that could anticipate potential problems and help us take preventative measures before they happen. This would improve the industrial robotic arm's efficiency and reliability and reduce maintenance costs while raising overall production. We succeeded in meeting the requirements, but in order to predict failures, a linear regression model is designed to predict the requirement of the maintenance on the basis of the dataset provided.

In summary, when it comes to digitizing operational insights that may be difficult to obtain through manual observation, LoRaWAN technology is invaluable. The potential for human-dependent processes to unintentionally ignore unconventional indicators highlights the significance of incorporating LoRaWAN technology. The benefits of using LoRa devices go beyond prevention; they provide the ability to rank maintenance tasks in order of importance. This involves supporting long- and mid-term maintenance plans in addition to proactive inspection techniques made possible by the early identification of anomalies. Thus, a more strategic and proactive approach to maintenance and operational management is made possible by the seamless integration of LoRaWAN.

Redefining the machine learning (ML) model and improving the prediction classifiers might be part of future work. This might involve examining the model architecture in greater detail, adjusting parameters, and improving the algorithm's performance. Furthermore, concentrating on reducing the scope of the prediction classifiers may result in a more precise and specialized model.