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Enhancement of Jaibot: Developing Safety and Monitoring Features for Jaibot Using IoT Technologies

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Abstract. The Hilti Jaibot, a state-of-the-art construction site drilling robot, has demonstrated remarkable productivity gains while also underscoring the need for improved safety and monitoring capabilities. This study aims to address this need by harnessing Internet of Things (IoT) technologies and predictive maintenance methodologies. The proposed enhancements encompass a comprehensive sensor and camera integration to monitor the robot's environment, coupled with the development of a Long Short-Term Memory (LSTM) predictive maintenance algorithm to preemptively identify operational issues. These improvements enable the Jaibot to autonomously detect and mitigate risks, such as obstacles and human activity, while providing real-time safety alerts to operators. Incorporating quantitative results from our predictive model, which successfully predicts three output variables (X, Y, and Z) using three input variables, we observed varying RMSE and MAPE values. Specifically, X exhibited an RMSE of 77.80% and a MAPE of 242.20%, while Y showed an RMSE of 31.10% and a MAPE of 69.70%, and Z had an RMSE of 34.53% and a MAPE of 82.74%. Notably, Y and Z data displayed high MAPE values, potentially attributed to data inconsistency. To enhance accuracy in our predictive model, we propose the utilization of more complex models and increased data volumes, which may mitigate the observed inconsistencies and lead to improved overall model performance. These findings from our quantitative analysis provide valuable insights for the integration of predictive maintenance algorithms into the Hilti Jaibot and lay the foundation for future advancements in robotic construction, emphasizing the pivotal role of IoT technology and predictive maintenance in shaping the industry's trajectory.

Keywords: AWS; Digital Twin; Hilti Jaibot; IoT; LSTM Predictive Model

1. Introduction

As the fourth industrial revolution, Industry 4.0 is progressing exponentially, and digital transformation and automation have gradually become a common phenomenon around us. Digitization, automation, and integration enhance productivity and improve the design and quality of the construction (Rabbani and Foo, 2022; Chong *et al.*, 2022; Yet, Lau, Thang 2022; PwC, 2016). However, the adoption of emerging technologies and automation within the construction industry is fairly slow relative to other industries. This is because of the inability to embrace technological advances relative to other industries, such as manufacturing and automotive. (Ma, Mao, and Liu, 2022) found that the complexity and decentralization of construction activities have resulted in the construction industry

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lagging behind compared to streamlined industries. Not only that, but the construction industry is also experiencing a skilled labor shortage of engineers, consultants, and supervisors, which result in project delays and eventually leads to a decrement in productivity and an increment in cost on the construction site (Jonny, Kriswanto, and Toshio, 2021).

In accordance with Hilti, the link between digitalization and job site has been accomplished as they bring digital solutions on-site and solve installation challenges by introducing the Hilti Jaibot, a semi-autonomous drilling robot for overhead installation with the aids of Building Information Model (BIM). The solution has helped contractors adapt to the changing phase of modern construction and furthermore brought value in terms of performance, innovation, and health and safety. According to research, Hilti Jaibot has improved the overall drilling accuracy by 50% and schedule reduction of 20% (Brosque and Fischer, 2022). This marks a significant step for the construction industry in addressing major challenges, including a shortage of skilled labor, stagnant productivity, and health and safety issues.

While the Hilti Jaibot is currently a cutting-edge construction robot, it's important to acknowledge that emerging technologies can surpass it if we neglect to integrate new innovations. Meeting the growing global demand for digital solutions with enhanced functionality and accessibility is essential to avoid obsolescence. The introduction of IoT technologies like Edge Computing, Big Data, and Digital Twin can boost productivity by enhancing the existing product. By leveraging IoT, we can optimize data and integrate machine learning and machine vision to enhance Jaibot's capabilities.

2. Related Works

The presence of the semi-autonomous Hilti Jaibot has addressed safety concerns and stagnant labor productivity issues in construction activities (Lee *et al.*, 2022). However, the Jaibot itself has not been implemented with IoT to provide assistance with overhead installation on the site. Without IoT support, the ability to move data over a network without the need for human or human interaction with the computer is not available. Since there is no involvement of IoT, the real-time information is unable to be ingested into the cloud for further processing, such as progress monitoring, computation of follow-up action, predictive maintenance, etc. (Thea, Lau, and Lai, 2022; Shen, Lukose, and Young, 2021). In accordance with the statement above, the supervisor or project manager may find it difficult to manage and monitor the progress and performance of the Jaibot on the construction site. Based on research, with inefficient and inaccurate progress monitoring, time and cost overruns may accounted for in construction projects (Omar, Mahdjoubi, Kheder, 2018). In the long run, the excessive loss of time and money may arise as a serious issue due to a lack of IoT technology implementation and result in the shutdown of a project in worst case scenario.

Other than that, the influence of Covid-19 on construction activities has resulted in the practice of remote working to limit the spread of disease. According to (Chin *et al.*, 2022; Fabiani *et al.*, 2021), the most effective policy to address the well-known need for worker distancing is to perform remote work. This makes the monitoring of Jaibot even harder compared to pre-pandemic times, where robots and equipment could be accessed by workers physically. The lack of remote monitoring aspect has reduced the productivity of the construction activities due to the social distancing policy on the site.

Over and above, due to its semi-autonomous operating system, the handling of an operator is essential to move the Jaibot from one point to another without any assistance from sensors. This indicates that there is a possibility that the Jaibot will crash into someone and result in minor casualties while moving on-site. From 2009 to 2019, there were around 400 robot-related accident cases reported in Korea (Lee, Shin, and Lim, 2021). Additionally, based on research found, (Villani *et al.,* 2018) write that: "Safety issues are the primary main challenge that must be tackled by any approach implementing collaboration between humans and robots." Worker safety is directly linked to site productivity since health and safety issues can impact the workforce. Consequently, prioritizing workplace robot safety in construction sites is crucial to prevent incidents that could pose risks to project progress.

3. Research Problem

The shortcoming of the Jaibot has presented to us as the connection between the cloud and Jaibot is insignificant due to the lack of IoT. This results in data loss, which prevents the processing of real-time information for better use cases such as data analytics, data optimization, data monitoring, etc., that may improve the efficiency and productivity of the robot. Implementation and integration of IoT into the Jaibot help to promote the intelligence of the robot for better performance, which accounted for one of the Hilti IoT long-term visions, "Smartization," to make the robot smarter in short. According to (Carvalho and Soares, 2019), progress monitoring is essential in construction management to reduce reworks and errors. The statement made above has shown the necessity of a progress monitoring feature on the Jaibot itself. Occurrences of overruns onsite in terms of money and time can be resolved by collecting, analyzing, and optimizing real-time data from the Jaibot. Additionally, the utilization of data has promoted the development of predictive maintenance or remote monitoring for improving the robot performance in terms of productivity and efficiency.

Besides that, the unique, dynamic, and complex nature of construction projects is likely to increase worker exposure to hazardous workplaces (Paneru and Jeelani, 2021). Not to mention the addition of a robot onsite that would result in an increment of health and safety issues due to high force robotic arm. To address the issue, physical or sensor-based barriers are frequently used in robotic automation systems to prevent any potentially dangerous situations when humans and robots interact. (Paneru and Jeelani, 2021) also states that the potential approaches of machine vision is presented to improve the health and safety monitoring practices. Machine vision technology can be applied to the development of obstacle detection, which brings the ability to detect obstacles or humans around the robot. This can greatly reduce the health and safety issues while interact with the robot onsite as the robot is able to determine the presence around it.

4. Methodology

For software configuration, Amazon Web Services (AWS) is used for software integration as it provides various services ranging from cloud servers to IoT platform services. With the aid of AWS, one of the services, IoT Greengrass provides the edge computing implementation to the Raspberry Pi; thus, the Raspberry Pi is able to communicate with the cloud while having the benefit of local processing while offline. The collected data from the sensors will be fed into the AWS IoT Core and S3 bucket in different protocols for different uploading methods. Then these data will be fed to the AWS IoT SiteWise using microservices called AWS Lambda to route the data to selected cloud services. IoT SiteWise is able to collect, organize and analyze data from the Raspberry Pi itself. Furthermore, AWS IoT Twinmaker is integrated into the system, where the digital twin is developed by importing the 3D model of the robot and the construction site. With the integration of IoT Greengrass, IoT Core, IoT SiteWise, and IoT Twinmaker, the digital twin of the Raspberry Pi (mimicking Jaibot) can be represented in the Grafana dashboard, along with the internal data such as video stream, detected distance, robot status, and other time-based data. The involvement of Machine Learning has provided the predictive maintenance feature and forecast the time-based data for the robot use cases.

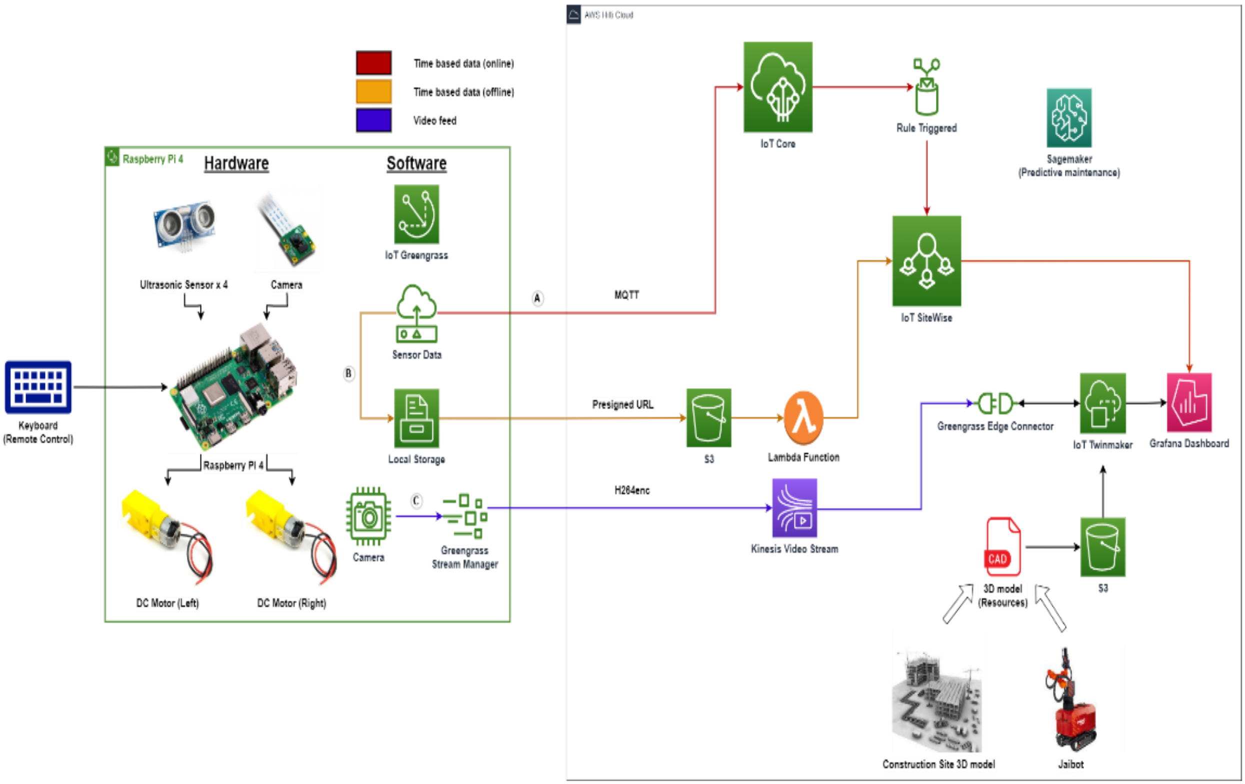

Figure 1 System Block Diagram

There will be three major systems surrounding the overall project which are:

- Remote data collection system
- Predictive maintenance system
- Obstacle detection & and avoidance system.

Digital twin technology creates virtual models of physical objects, like our robot. Unlike simulations, digital twins are real-time interactive environments. Sensors on the physical object gather data and transmit it to the digital twin, enabling real-time optimization, performance monitoring, problem identification, and solutions testing without real-world risks.

In predictive maintenance, we utilize LSTM for feature extraction from Big Data comprising multi-sensor parameters. Deep learning on high-dimensional information aids Remaining Useful Life (RUL) prediction. Here are the LSTM model equations shown in equation 1-6:

$$f_t = \lambda\{W_f \cdot [y_{t-1}, x_t] + b_f\} \quad (1)$$

$$\widetilde{C}_t = tanh\{W_c \cdot [y_{t-1}, x_t] + b_c\} \quad (2)$$

$$i_t = \lambda\{W_i \cdot [y_{t-1}, x_t] + b_i\} \quad (3)$$

$$C_t = f_t C_{t-1} + i_t \widetilde{C}_t \quad (4)$$

$$O_t = \lambda\{W_o \cdot [y_{t-1}, x_t] + b_o\} \quad (5)$$

$$y_t = O_t \tanh(C_t) \quad (6)$$

where f_t = forget gate, $i_t =$ input gate, O_t = output gate, C_t = long-term memory, y_t = short-term memory, x_t and x_t' = input and output at time t, λ, and tanh = activation functions, $\widetilde{C_t}$ = selection of long-term memory at time t, W = weight, and b = deviation

In theory, the data is preprocessed before the training process by using normalization processing to reduce noise and prediction error. After the training of data, the mapped HI is conducive to the evaluation of the health status. Furthermore, a degradation curve within the service life is produced, and the RUL is predicted. To calculate the evaluation indexes of the trained model, RSME, MAPE, and R^2 is used where the smaller the RSME value, the better the performance; the closer the R^2 is to 1, the better the data fits and outcomes. The formula of RSME, MAPE and R^2 is shown in equation 7, 8 and 9 respectively.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{actual} - y_{predict})^2} \tag{7}$$

$$MAPE = median\frac{(|y_{actual} - y_{predict}|)}{y_{actual}} \tag{8}$$

$$R^2 = 1 - \frac{\sum(Y_{actual} - Y_{predict})^2}{\sum(Y_{actual} - Y_{mean})^2} \tag{9}$$

The implementation of the ultrasonic sensor is associated with the feature of detecting and avoiding obstacles. In theory, similar to radar, the fundamental working principle of ultrasonic sensors is to emit high-frequency sound waves with an emitter and receive the reflected sound waves with a receiver. Based on the time required for the sound waves to be reflected back, the distance can be calculated using equation 10, where T is the time required, and C is the speed of sound.

$$Distance = \frac{1}{2}T \times C \tag{10}$$

The speed of sound, typically 343m/s at 20°C, varies with temperature and humidity. Ultrasonic sensors enable the robot to detect obstacles, even transparent ones like clear plastic. AWS IoT Twinmaker creates digital twins of real-world systems, enhancing operations. Using existing data and 3D models, the Jaibot and the construction building are input into the IoT Twinmaker scene in this project (see Figure 2).

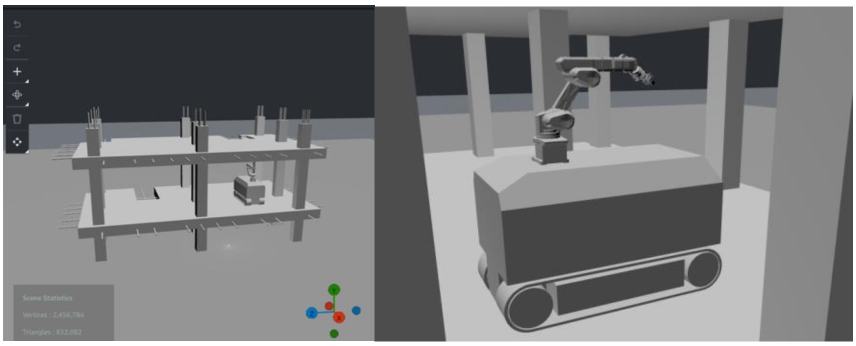

Figure 2 AWS IoT Twinmaker Scene & 3D Model Jaibot

Figure 2 illustrates the 3D environment of the developed digital twin of a Jaibot and the site scene. The 3D model of the Jaibot and the environment is inserted in AWS Twinmaker, where the 3D environment is generated accordingly. The 3D models, along with the lighting, can be transformed into different positions, rotations, and scales according to the use cases in the scene for representing the real Jaibot in a remote construction site.

The LSTM predictive maintenance model is trained using MATLAB (Figure 3). Four out of five vibration datasets (X, Y, Z) are used to train, test, and validate the model, aiming to monitor drill bit abnormalities during long working periods. Input data is pre-processed, split into sequences, and model architecture is configured with editable parameters. Performance is evaluated using RMSE and MAPE values, and the predicted results are compared against the actual results. Tuning involves adjusting hyperparameters to prevent overfitting while maintaining a balance between data and model architecture.

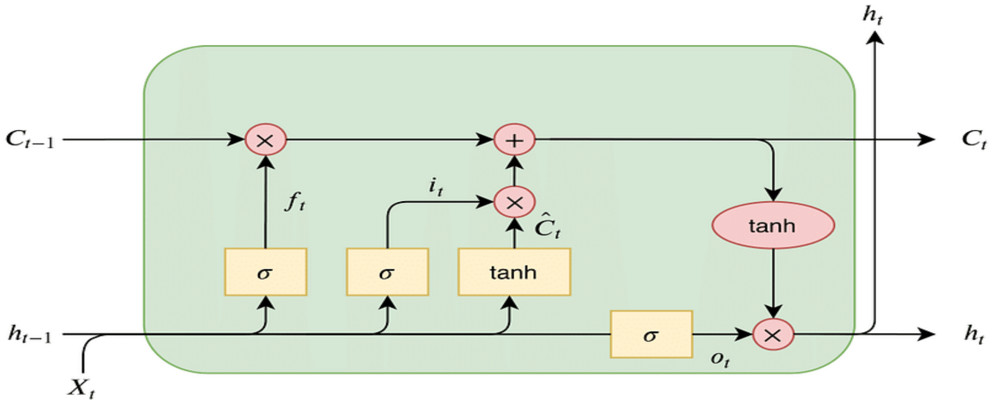

Figure 3 LSTM Predictive Maintenance Model

5. Testing and Evaluation

The first test is experimented with the method of data uploading in order to indicate the time required to upload the IoT data to the cloud. According to the block diagram, there are two different methods of sending the data to the cloud, which are implementing MQTT and HTTPS protocols for JSON files and CSV files. In this test, the time for uploading the data to the cloud for each method is collected and tabulated into the table below by using the code of the response.elapsed.total_seconds().

Table 1 Efficiency Test of Different Uploading Method

Attempts	MQTT protocol - JSON file (second)	HTTPS protocol - CSV file (second)
1	1	1.2381
2	1	1.2154
3	1	1.6699
4	1	1.2112
5	1	1.1709
Average	1 second	1.3011 seconds

According to the results shown in Table 1, the MQTT protocol takes less time to upload data to the cloud than the HTTPS protocol. However, it should be mentioned that the HTTPS protocol has a higher efficiency than the MQTT protocol. This is because the MQTT protocol can only upload a single batch of data to the cloud at a time, whereas the HTTPS protocol can send a single or multiple batches of data to the cloud. Moreover, since the use case of the robot is designed to operate in a remote environment, the HTTPS protocol would be a greater approach for data uploading to the cloud after an internet connection is available.

The second test experimented on the data uploading speed on different sizes of the CSV file through HTTPS protocol. Since the use case of the robot is mainly operated in a remote area where the connection is unstable, therefore the data is most probably initially stored locally inside the robot until the robot has a stable internet connection. The uploading speed of the data is essential to the digital twin of the robot in a virtual environment where the users want to manage and optimize real-time data. Thus, this testing is conducted to identify the size of the data affecting the uploading speed.

Table 2 displays the experimental results for data uploads utilizing the HTTPS protocol for varied data sizes ranging from KBs to MBs. Despite the large disparity in data volumes, the upload speed for both instances remained under 2 seconds on average. This implies that while data size has an impact on the upload speed, the impact is not significant enough to affect the speed in terms of seconds.

Table 2 Speed Test of Different Data Size

Attempts	Small-sized data (second)	Large sized data (second)
1	1.4540	2.0931
2	1.1757	1.7493
3	1.3733	1.8037
4	1.2669	1.8467
5	1.2225	1.8408
Average	1.2985 seconds	1.8667 seconds

The third testing is conducted on testing the video streaming features where the process would experience some delay due to various factors such as video resolution, video format, type of encoder, and more. In the system implementation, the video is streaming with the H.264 (AVC) encoder, as it is a video compression standard used in digital video content. Likewise, the H.265 (HEVC) encoder works the same way as H.264 but is newer and more advanced in several ways. Thus, in this testing, these two encoders will be compared in terms of bandwidths, streaming time delay, frame rate, and allocated storage byte size.

Table 3 reveals differences between H.264 and H.265 encoders. H.265 excels in bandwidth and storage efficiency, while H.264 suits real-time video streaming. For this project, H.265 is preferred for remote operations with limited bandwidth and storage. Testing four focuses on LSTM model accuracy for system failure prevention. Fine-tuning training options aim to minimize RMSE and MAPE values, ensuring high accuracy. Table 4 shows that increasing LSTM layer size and epochs generally improves prediction performance for smaller data sizes. Performance varies among output variables, with X being the most challenging to predict. Results indicate the LSTM model's suitability varies based on data and tasks. In the final test (Testing 5), obstacle detection and avoidance system reaction time are assessed in stopping movement within threshold values.

Table 3 Testing Between H.264 and H.265 Encoder

Parameters	H.264	H.265
Bandwidths (kbps)	236.14	120.11
Time delay (s)	9.2	9.8
Frame rate (fps)	14.2473	14.4481
Allocated storage byte size (kb)	136.07	90.77

In five tests, the system achieved an average reaction time of 0.146 seconds and covered an average distance of 5.22 cm. These results demonstrate the system's swift response to detected obstacles, ensuring quick recognition and avoidance. The short stopping distance enhances safety by preventing collisions and potential damage. Overall, the system proves its effectiveness in recognizing and reacting to obstacles, enhancing secure robotic navigation.

Table 4 Model Accuracy Test

Data Size	LSTM Layer	Epochs	RMSE (%)			MAPE (%)		
			X	Y	Z	X	Y	Z
100	100	100	108.99	31.46	34.85	305.14	38.32	75.03
		200	118.06	32.65	37.79	438.26	44.23	100.44
		300	158.60	36.03	37.90	631.28	52.44	83.60
	200	100	90.30	31.46	33.89	229.82	40.36	70.12
		200	136.00	33.69	37.96	486.48	44.45	75.27
		300	138.80	36.54	38.77	450.49	54.11	103.90
	300	100	106.12	32.75	37.00	322.14	43.74	80.07
		200	124.38	32.42	40.73	381.41	41.67	86.61
		300	146.11	40.19	42.01	551.99	52.16	87.59
200	100	100	81.52	30.07	33.43	261.42	67.84	82.18
		200	84.46	31.31	34.26	258.78	56.69	82.39
		300	81.99	29.25	34.68	280.65	75.67	87.39
	200	100	81.38	31.35	34.40	266.80	67.88	80.56
		200	80.66	34.28	34.77	273.22	97.70	86.36
		300	86.53	30.81	37.76	298.83	82.35	89.73
	300	100	81.90	31.32	34.26	243.87	62.38	79.10
		200	83.47	30.18	33.8	290.32	63.83	81.27
		300	103.01	33.70	39.09	400.85	84.13	96.63
500	100	100	88.38	37.29	36.15	246.94	52.29	154.90
		200	87.12	36.92	36.54	244.42	50.33	144.89
		300	89.36	37.20	38.31	264.40	54.93	147.65
	200	100	86.86	38.11	35.48	239.66	53.84	144.31
		200	86.87	37.12	38.26	247.33	51.73	161.45
		300	90.74	37.42	38.41	273.70	58.02	129.42
	300	100	86.48	37.67	36.33	239.58	52.55	141.03
		200	86.22	36.91	37.65	249.87	53.06	152.47
		300	88.36	37.04	37.54	259.24	51.79	140.31
1000	100	100	83.22	34.61	33.74	426.07	68.09	172.18
		200	81.30	34.39	34.72	404.03	64.07	158.82
		300	81.57	34.30	33.80	385.22	57.86	139.80
	200	100	81.88	35.46	33.83	414.41	64.39	163.48
		200	81.72	35.14	34.54	405.75	60.09	145.73
		300	81.90	35.07	34.54	399.05	58.83	134.06
	300	100	82.32	35.40	34.93	421.13	62.30	175.77
		200	82.13	35.68	33.70	387.94	59.19	134.69
		300	80.42	35.21	33.04	369.45	53.18	129.31

After the data is imported, the data will be displayed in the dashboard, where it is shown in Figure 4. The left side of the dashboard shows the parameters of date and time, average CPU temperature, and CPU speed. In addition, the values from the ultrasonic sensors, along with an obstacle alarm, are also displayed on the other side of the dashboard. Video stream from KVS and 3D scenes from IoT Twinmaker are also imported into the dashboard, thus; the user is able to view the camera feed from the robot and the digital twin of the robot in virtual environment.

Table 5 Obstacle Detection & Avoidance Precision Test

Attempts	Reaction time (second)	Travel distance after the trigger of ultrasonic sensor (cm)
1	0.13	5.0
2	0.15	5.3
3	0.15	5.3
4	0.16	5.2
5	0.16	5.3
Average	0.146	5.22

The LSTM model successfully predicts three output variables (X, Y, and Z) using three input variables. Despite achieving successful predictions in Figure 5, varying RMSE and MAPE values are observed. The model is configured with 500 data size, 200 LSTM layers, and 200 epochs, resulting in different accuracy levels: X (RMSE 77.80%, MAPE 242.20%), Y (RMSE 31.10%, MAPE 69.70%), and Z (RMSE 34.53%, MAPE 82.74%). Notably, Y and Z data exhibit high MAPE values, possibly due to their data's inconsistency. To enhance accuracy, using more complex models with increased data may mitigate this issue, boosting overall model performance.

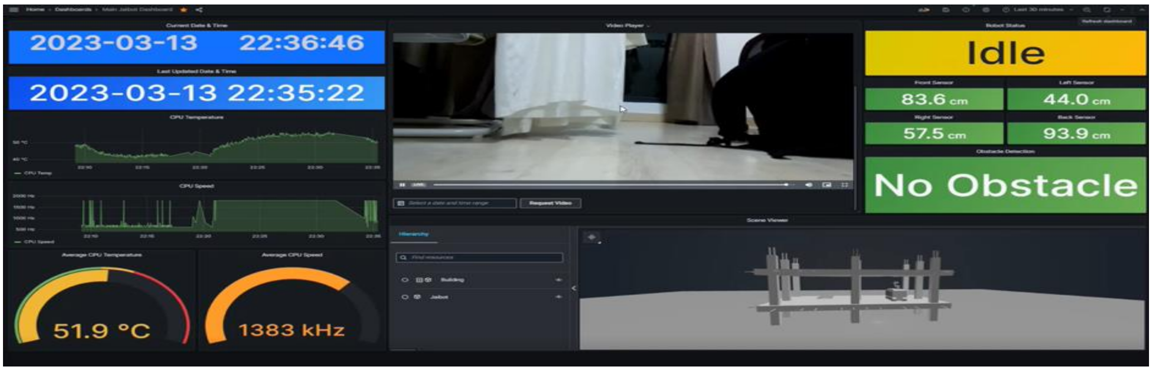

Figure 4 Grafana Dashboard Console

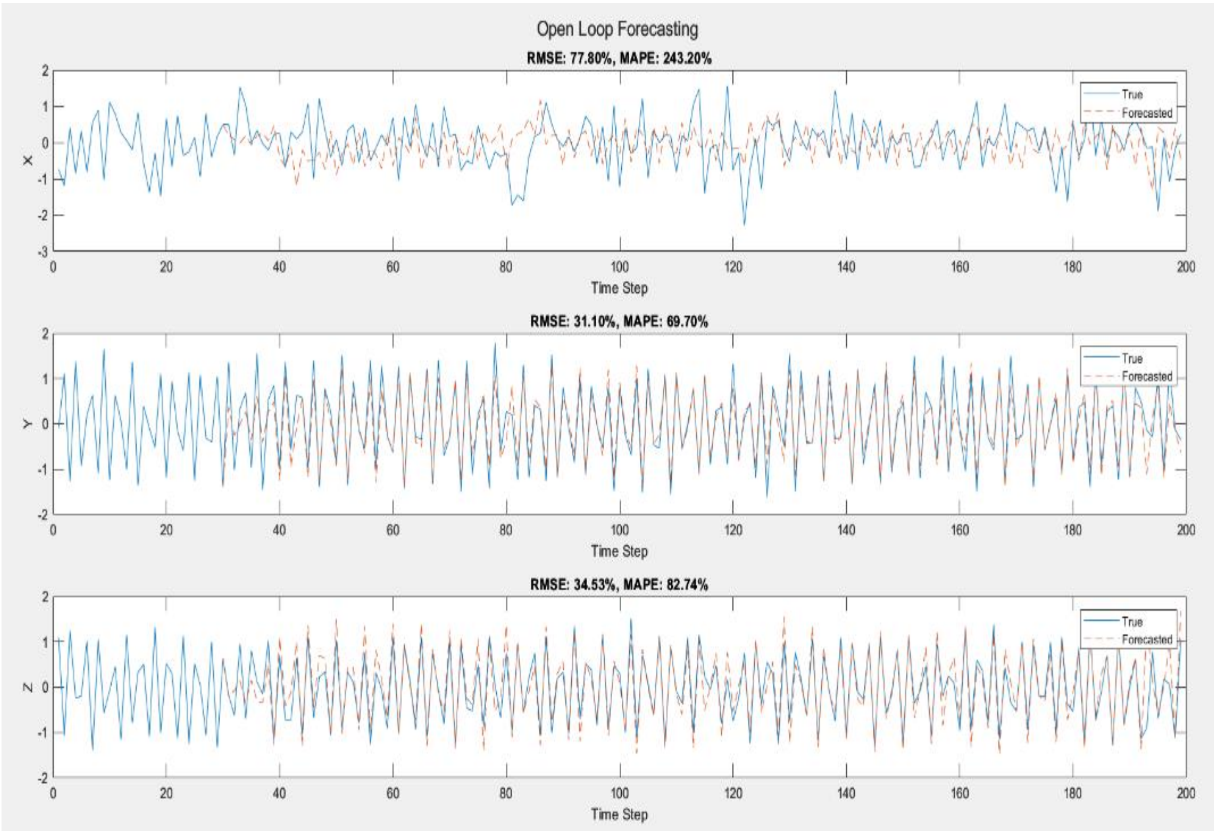

Figure 5 Plot of Actual and Forecast Data

6. Conclusion and Future Works

In summary, this project aimed to enhance Jaibot's capabilities through machine learning, machine vision, and IoT, with three key objectives: implementing predictive maintenance, developing obstacle detection with ultrasonic technology, and rigorously evaluating system reliability, encompassing real-world performance factors such as speed, accuracy, and durability. Beyond these achievements, the project holds broader significance, as integrating IoT into Jaibot creates opportunities in logistics, agriculture, and healthcare, with future directions potentially involving advanced AI algorithms and renewable energy sources to expand operational capabilities. The challenges identified in this project serve as inspiration for further innovation in robotics and IoT. In conclusion, our project not only met its objectives but also demonstrated the transformative potential of IoT in autonomous robotics, positioning Jaibot's enhancements as a catalyst for progress, promising a safer and more efficient future in robotics and beyond.

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