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A digital twin framework for predictive slurry pump diagnostics in mining operations

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Abstract

A digital twin is a virtual representation of a physical component, part, or system created by collecting and analysing data from sensors and other connected devices. The development of a digital twin for slurry pumps in a mineral processing plant can improve pump reliability and efficiency, leading to reduced downtime, cost savings, and increased plant productivity. Recent advances in sensors, the Internet of Things, and Artificial Intelligence have made it possible to monitor machinery continuously and analyse large quantities of operating data in real time. This paper presents the design and prototype development of a digital twin for a centrifugal slurry pump. The digital twin is hosted locally on a web page developed in Microsoft Visual Studio Code using JavaScript, while sensor data are transmitted to a microcontroller and communicated to the web application through the Message Queuing Telemetry Transport protocol. A machine learning model developed in Google Colab using a Python Jupyter notebook monitors the incoming data and provides insights into pump health. The system supports real-time performance monitoring, anomaly detection, failure prediction, alert logging, and maintenance scheduling. By linking a 3D virtual model to live operating conditions, the proposed digital twin enables remote monitoring of slurry pump behaviour and provides a practical foundation for predictive maintenance in mining processing plants.

Keywords: Digital twin; Slurry pump; Fault diagnosis; Machine learning; Artificial intelligence; Predictive maintenance

1. Introduction

In mineral processing plants, slurry fluids must be transported across the facility for subsequent processing. Centrifugal slurry pumps are commonly used to move this fluid at the required pressure and flow rate for the extraction of valuable minerals. A centrifugal pump is a mechanical device that moves fluids by transferring rotational kinetic energy from a driven rotor into hydraulic energy [1]. During operation, slurry pumps are exposed to mechanical stress, elevated temperatures, excessive vibration, and component wear, all of which can lead to degradation and failure if they are not properly managed [2]. Failure of this equipment causes prolonged downtime, reduces productivity, and results in financial loss. Rapid developments in the Industrial Internet of Things (IIoT) and Artificial Intelligence now enable large volumes of sensor data to be transferred, stored, and analysed through cloud services for diagnosis and prediction of equipment behaviour using the digital twin concept [3-6].

According to Omar et al. [7], anomaly detection is the process of identifying data points that deviate significantly from normal standards. It is crucial for identifying potential failures and abnormal operating conditions. Machine learning algorithms such as support vector classification, as well as deep learning algorithms such as convolutional neural

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networks, can detect anomalies through clustering or statistical modelling and flag abnormal equipment behaviour for responsible personnel [8]. Time-series analysis is also useful because it enables data collected over time to be analysed and interpreted. In centrifugal pump digital twins, this approach can be used to analyse historical pump performance data and identify patterns, trends, and anomalies [9].

According to Liu et al. [3], a digital twin is a simulation concept that uses sensor updates and operational history from physical objects to create a virtual replica of a physical object or system. Digital twins can be developed using platforms such as MATLAB, Microsoft Azure Digital Twins, Siemens, and Oracle Digital Twin platforms, among others, as industrial technology companies continue to invest in this field. Digital twins enable users to monitor, predict, simulate, and test physical models remotely under real-world conditions at relatively low cost [10]. The application of digital twins to slurry pumps in the mining sector remains limited and is not yet fully explored. This paper therefore develops a digital twin for a centrifugal slurry pump in a processing plant to support proactive maintenance, failure prevention, and improved performance. The work includes sensor data acquisition, integration of data into a digital twin model, predictive analysis using machine learning algorithms, and a web-based application for data visualisation. The digital twin is intended to identify and analyse causes of pump failures, predict pump behaviour from available data, and provide real-time monitoring of pump health, although it is limited in direct control of the equipment. Its effectiveness is considered through failure prediction, reduction of unplanned downtime, and improvement of pump reliability.

2. Materials and Methods

2.1. Research Objectives

The objectives used to achieve the slurry pump digital twin are given as follows:

- To design a data-capturing system for pump operating conditions.
- To develop an algorithm to classify and predict data from the physical pump.
- To develop a three-dimensional virtual model of a centrifugal pump incorporating real-time sensor data.
- To develop a web-based application for real-time monitoring and predictive analytics of pump performance.
- To develop a centrifugal slurry pump digital twin prototype.

2.2. Methods

The methods and materials used to gather information, and the stages implemented to develop a digital twin for a 15-kW slurry pump in a processing plant, were based on a case study of a local gold mine in Zimbabwe. To meet the research objectives, the methods summarised in Table 1 were implemented.

Table 1 Research methods

Objectives	Tools
i	PLC Siemens S7, sensors, TIA software, Arduino software, literature review
ii	Jupyter, Anaconda, Python, machine learning algorithms
iii	CAD modelling and simulation — SolidWorks
iv	Python, JavaScript, CSS, HTML, Node.js software, literature review
v	ESP32 microcontroller, DHT22 sensors, vibration sensors, ACS712 current sensor, ZMPT101B voltage sensor, MQTT, web-based dashboard

Fig. 1 shows quantitative survey data using a questionnaire for the priority in customer requirements of a digital twin.

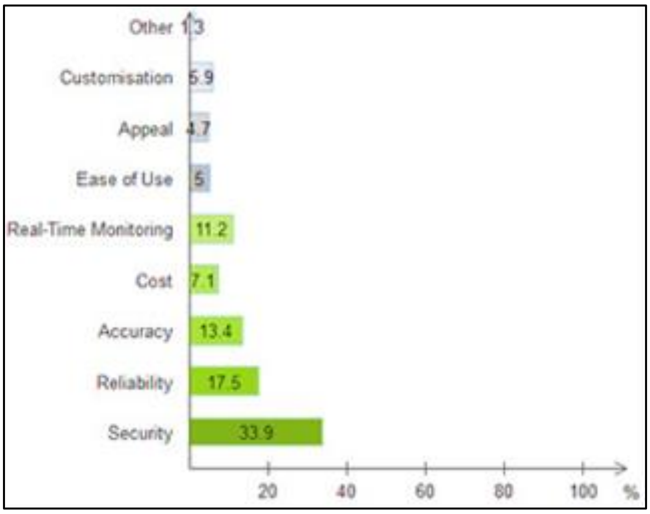


Figure 1 Customer requirements in a digital twin

3. System Design

3.1. System Overview

The system overview illustrated in Fig. 2 shows the proposed sensor mounting points on the equipment, the PLC controller connections, and the cloud-based machine learning model used for data classification and regression. The design enables monitoring and prediction of equipment performance from the physical pump to the virtual twin.

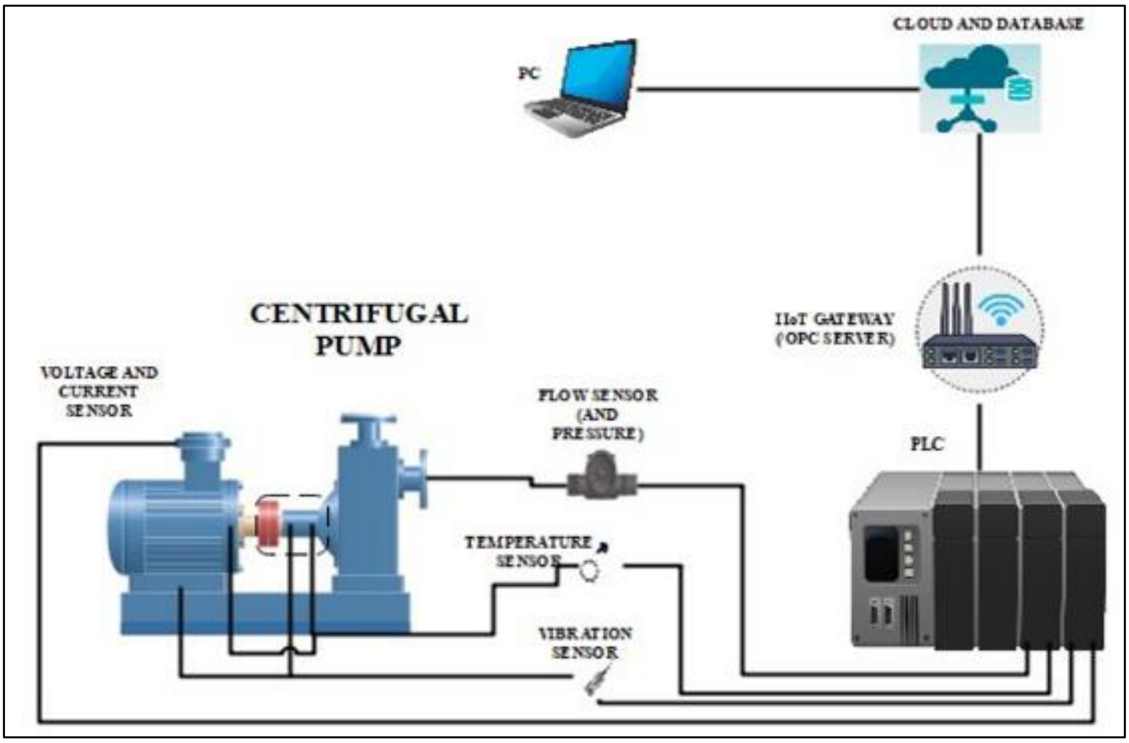


Figure 2 Slurry pump digital twin system design

3.2. Machine Learning Development

The machine learning model for slurry pump diagnosis and predictive analytics was developed in Python using a Jupyter-based notebook on Google Colab. A Long Short-Term Memory (LSTM) algorithm was selected because the pump condition data are time-dependent and the model needs to learn trends from sequential operating measurements.

4. Results and Discussion

4.1. PLC Simulation Results

The Allen-Bradley ControlLogix PLC at the mine processing plant is used to automate several items of equipment, including the slurry pumps. For integration with the digital twin system, it accepts sensor inputs through its input modules and provides outputs for actions required during pump operation. Sensor inputs are transferred from the PLC to an Industrial Internet of Things (IIoT) gateway, which transmits data to the cloud for machine learning diagnosis and predictive analytics. Siemens TIA Portal, shown in Fig. 3, was used to simulate system integration with multiple connected sensors.

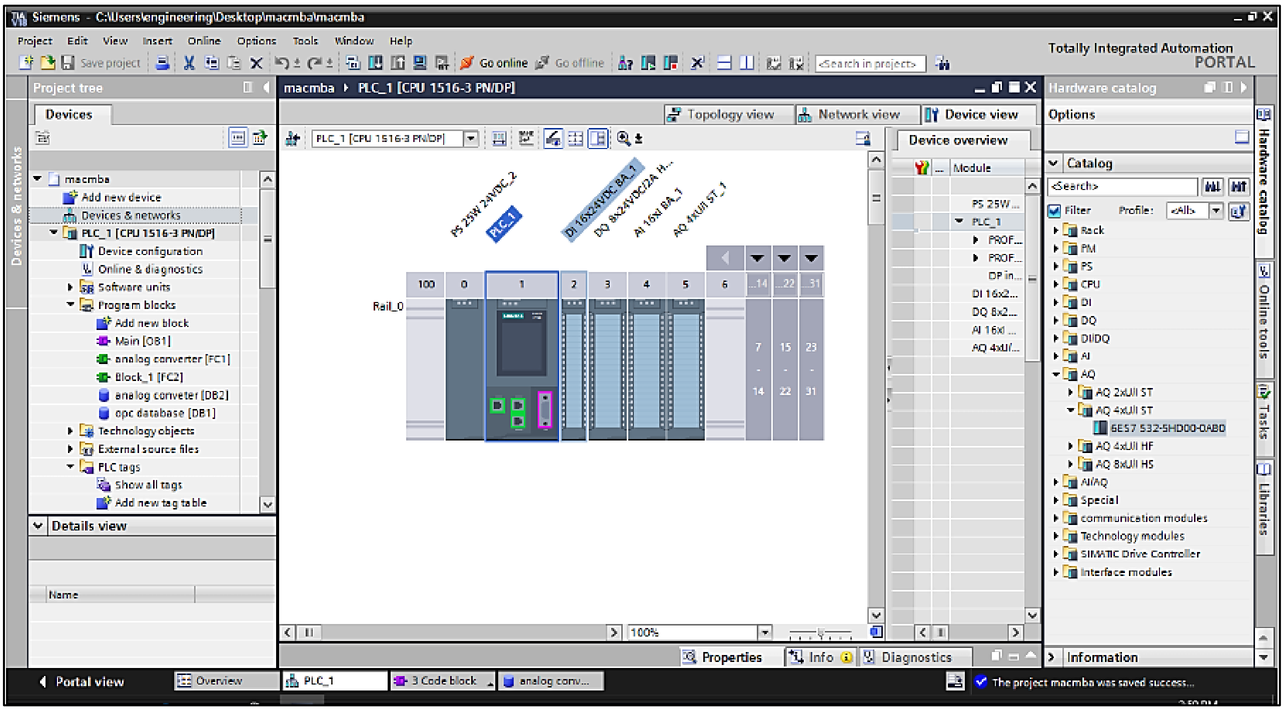


Figure 3 PLC simulated using Siemens TIA Portal

The simulated PLC results in Siemens SIMATIC S7 show how the ladder logic collects sensor data and checks pump health using voltage, current, vibration, and temperature measurements from the pump motor and bearing assembly coupling, as shown in Fig. 4.

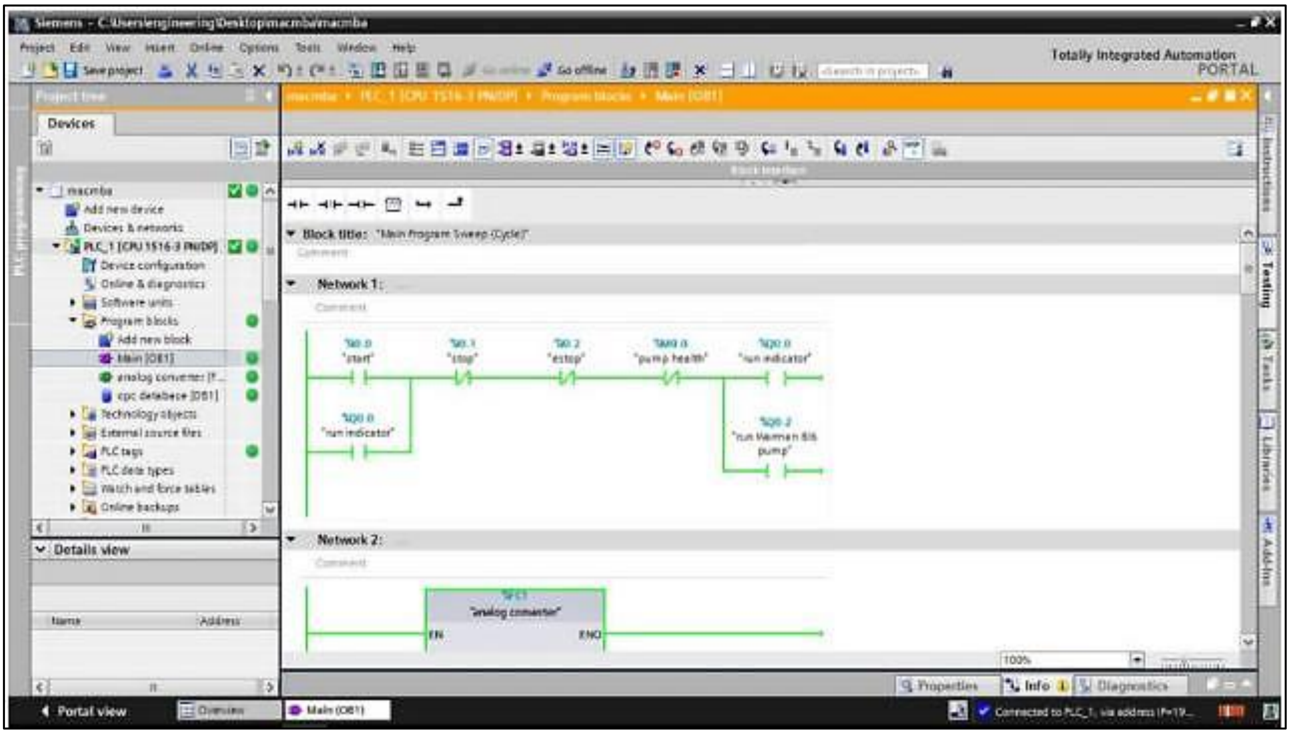


Figure 4 Simulated healthy pump status on network block 1

The data collected by the sensors are stored in the OPC database shown in Fig. 5. This database is used by the machine learning model for training and for historical documentation of the slurry pump's behaviour throughout its operating life.

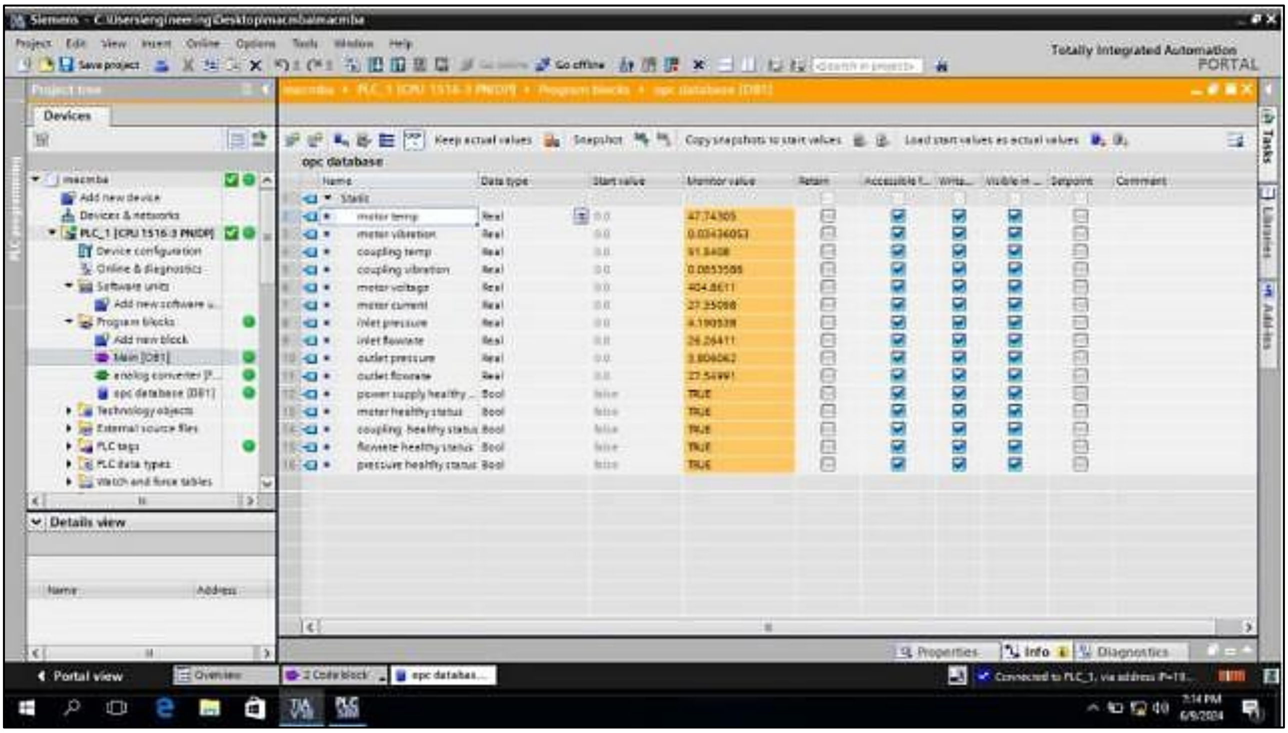


Figure 5 OPC database results

4.2. Prototype Design Setup

A prototype was designed to demonstrate the functionality of the slurry pump digital twin. The components used to collect data from a pump model included an ESP32 WeMos Lolin microcontroller, three DHT22 temperature and humidity sensors, two Arduino vibration sensors, an ACS712 current sensor, and a ZMPT101B voltage sensor. The circuit design diagram for the prototype is illustrated in Fig. 6.

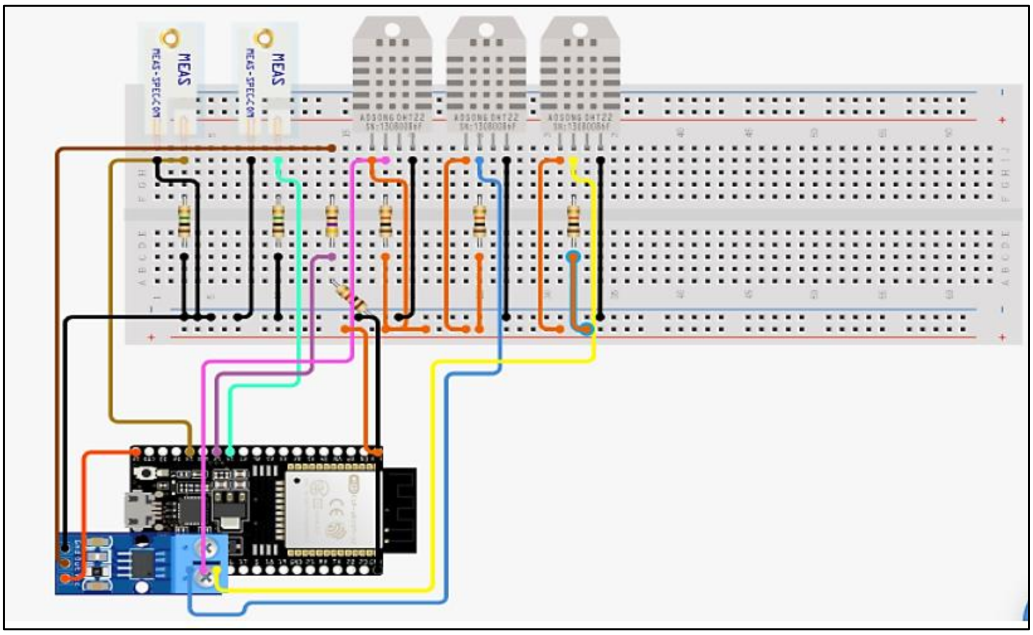


Figure 6 Microcontroller and sensor integration circuit

The developed data-collection sensor unit is shown in Fig. 7. It was mounted on a centrifugal pump to collect data and feed the virtual twin for diagnosis, machine learning model training, and analytics using the Message Queuing Telemetry Transport protocol.

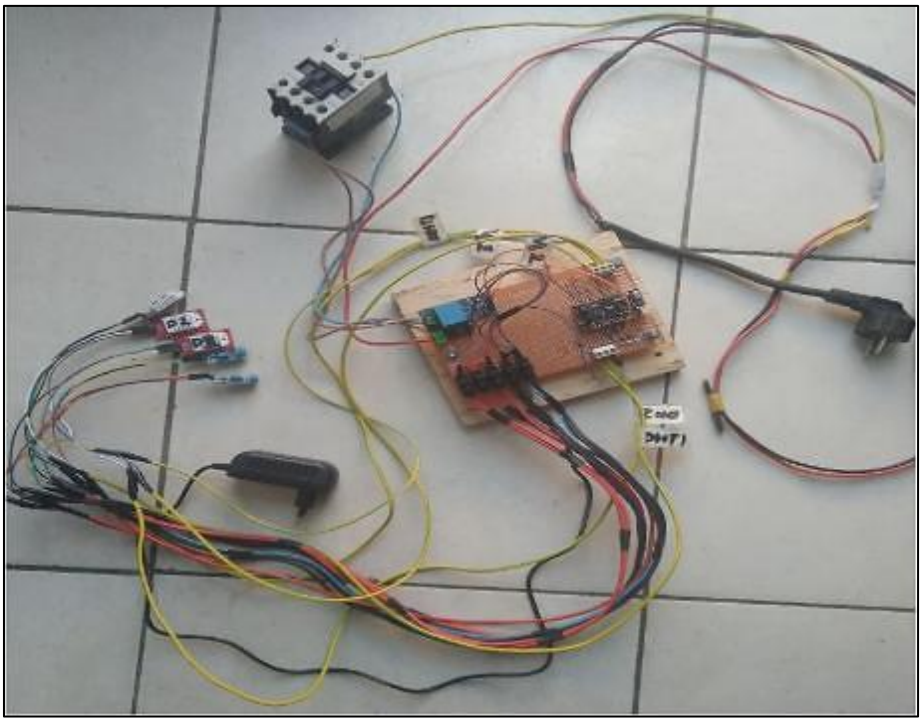


Figure 7 Connection of microcontroller and sensors

4.3. Data Generation

The generated dataset represents three years of operation for six pumps. Data were generated at 10-minute intervals to provide input data points for the LSTM algorithm. Fig. 8 shows a section of the data generated using Python.

```
Starting data generation for Pump ID: 0
Generating data for Pump ID: 0
Pump ID: 0 undergoing maintenance at 2021-09-28 14:48:15.056294
Pump ID: 0 undergoing maintenance at 2022-03-21 14:48:15.056294
Pump ID: 0 undergoing maintenance at 2022-08-19 14:48:15.056294
Pump ID: 0 undergoing maintenance at 2023-02-13 14:48:15.056294
Pump ID: 0 undergoing maintenance at 2023-07-03 14:48:15.056294
Pump ID: 0 undergoing maintenance at 2023-11-26 14:48:15.056294
Pump ID: 0 undergoing maintenance at 2024-04-23 14:48:15.056294
Data generation for Pump ID: 0 complete. Time taken: 4.37 seconds
Finished data generation for Pump ID: 0
Starting data generation for Pump ID: 1
Generating data for Pump ID: 1
Pump ID: 1 undergoing maintenance at 2021-09-29 14:48:15.056294
Pump ID: 1 undergoing maintenance at 2022-03-23 14:48:15.056294
Pump ID: 1 undergoing maintenance at 2022-07-13 14:48:15.056294
Pump ID: 1 undergoing maintenance at 2022-11-13 14:48:15.056294
Pump ID: 1 undergoing maintenance at 2023-03-13 14:48:15.056294
Pump ID: 1 undergoing maintenance at 2023-07-16 14:48:15.056294
```

Figure 8 Data generated using random function

The distribution of the dataset is illustrated graphically in Fig. 9, which was developed using Kaggle.

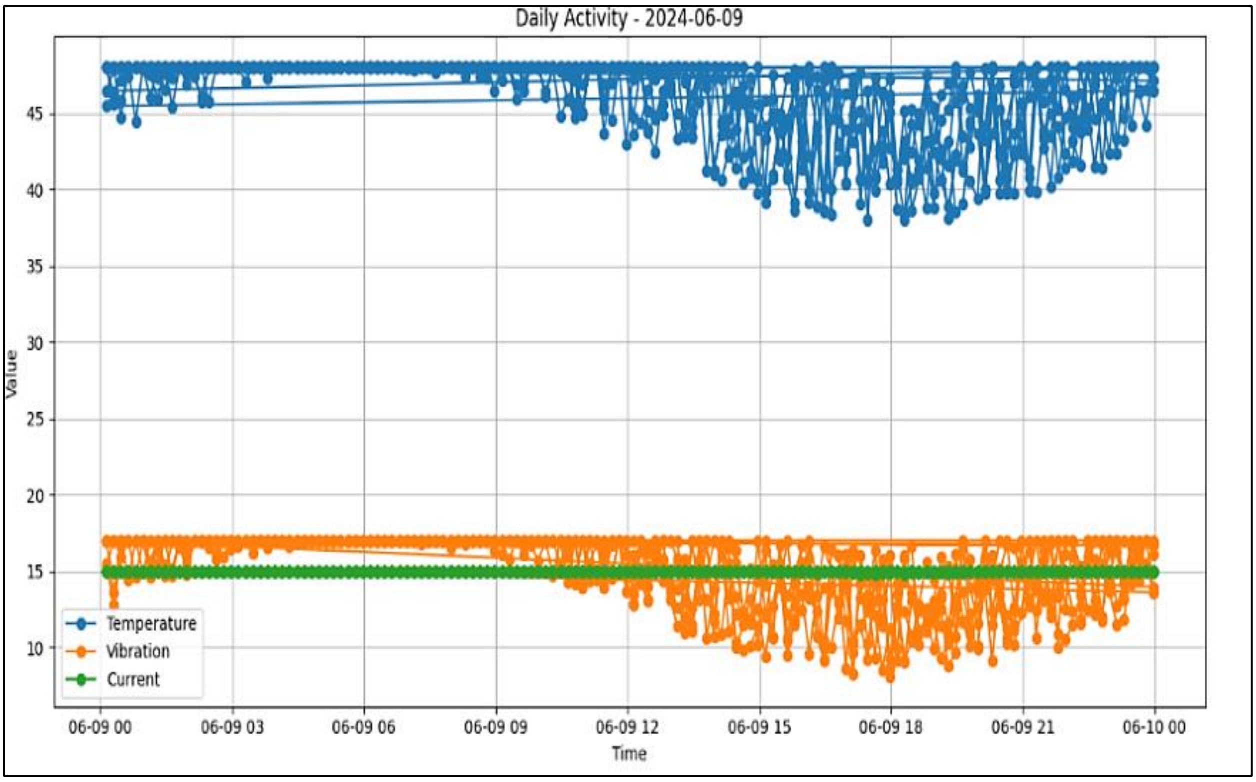


Figure 9 Summary plot of generated data points

4.4. Long Short-Term Memory (LSTM) Architecture

The summary of the LSTM model results is shown in Fig. 10. A Long Short-Term Memory algorithm was used to develop the machine learning model for anomaly detection and prediction of pump performance.

```
model.summary()

Building LSTM model
LSTM model building complete. Time taken: 0.28 seconds
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_2 (LSTM)               (None, 30, 64)            17408

 dropout_1 (Dropout)         (None, 30, 64)            0

 batch_normalization_1 (Bat  (None, 30, 64)            256
 chNormalization)

 lstm_3 (LSTM)               (None, 32)                12416

 dense (Dense)               (None, 3)                 99

=================================================================
Total params: 30179 (117.89 KB)
Trainable params: 30051 (117.39 KB)
Non-trainable params: 128 (512.00 Byte)
_________________________________________________________________
```

Figure 10 LSTM model building summary

4.5. Slurry Pump Digital Twin

The interactive 3D model shown in Fig. 11 incorporates real-time sensor data on slurry pump motor operating conditions, including temperature, vibration, and current.

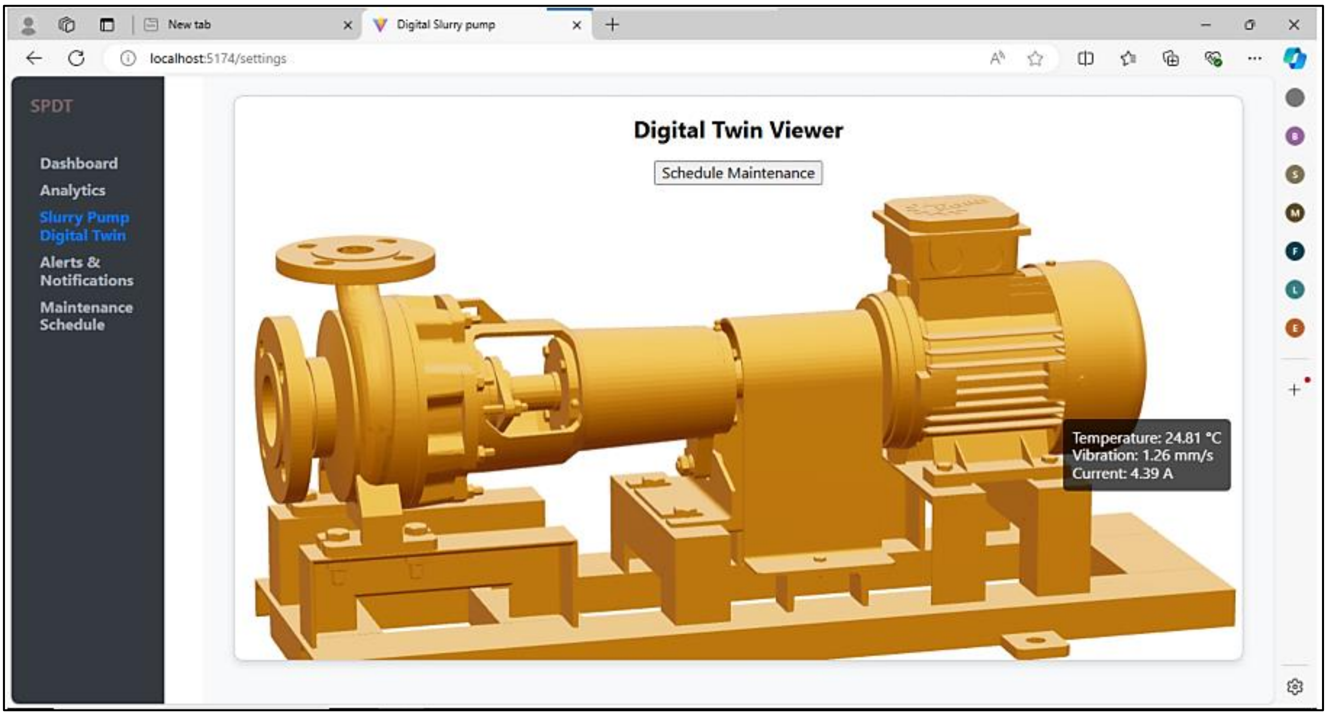


Figure 11 Slurry pump digital twin incorporating real-time sensor data

Figure 12 shows that the digital twin also incorporates the ambient conditions in which the slurry pump operates.

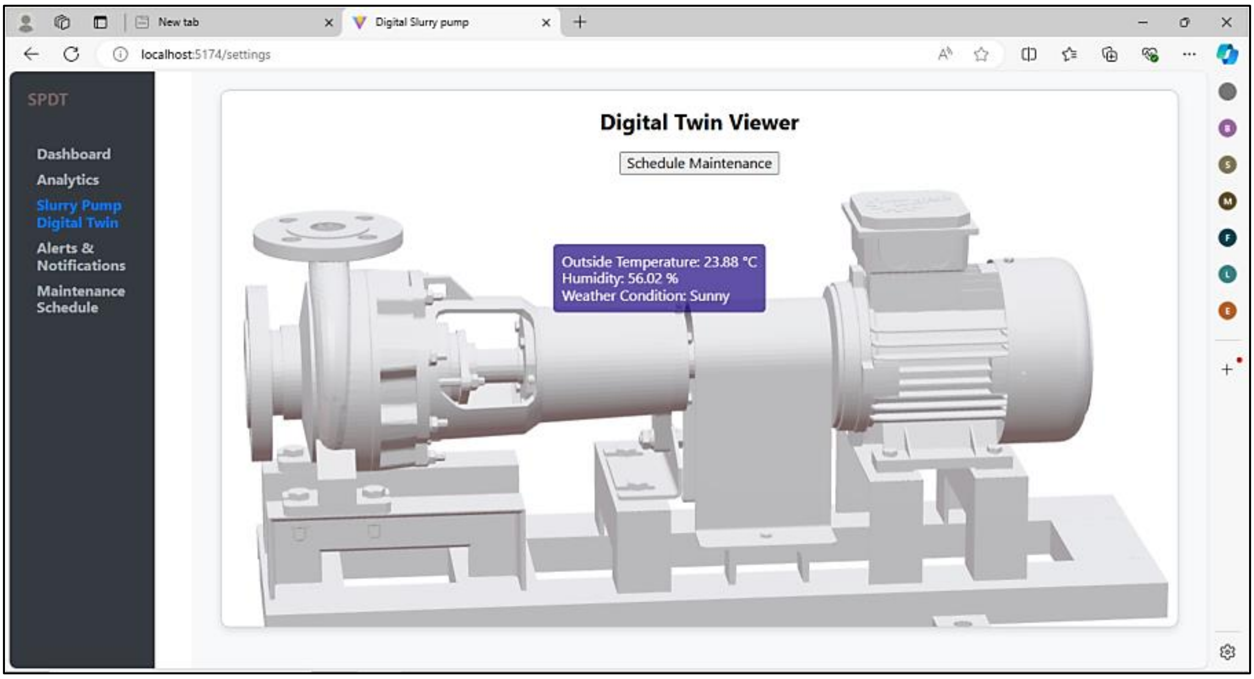


Figure 12 Slurry pump digital twin incorporating ambient conditions

4.6. Machine Learning Diagnosis and Data Analytics

Alerts and notifications are generated when specified operating thresholds for pump condition are exceeded, and the system states the appropriate action to be taken.

4.6.1. Real-Time Pump Diagnosis

Colour coding was implemented to make pump condition easy to interpret: green indicates normal operation, yellow indicates minor issues, orange indicates warning conditions, and red indicates critical conditions requiring immediate action. The critical pump motor vibration warning is illustrated in Fig. 13. Pump system statuses were recorded and stored for prediction and for tracking persistent component faults during diagnosis.

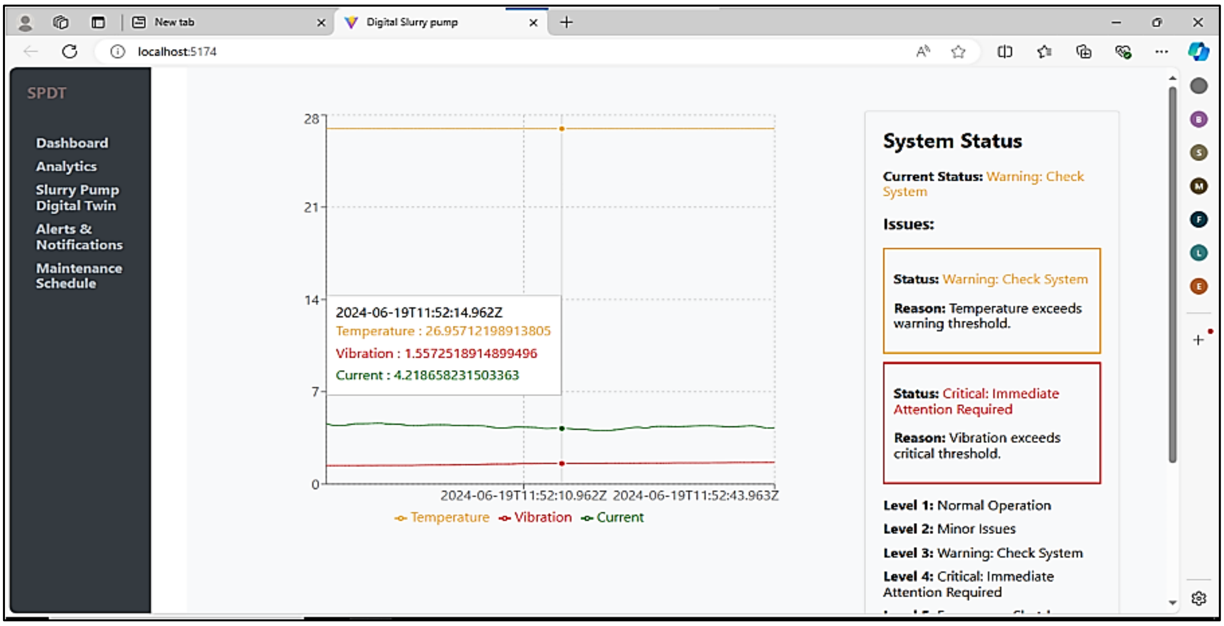
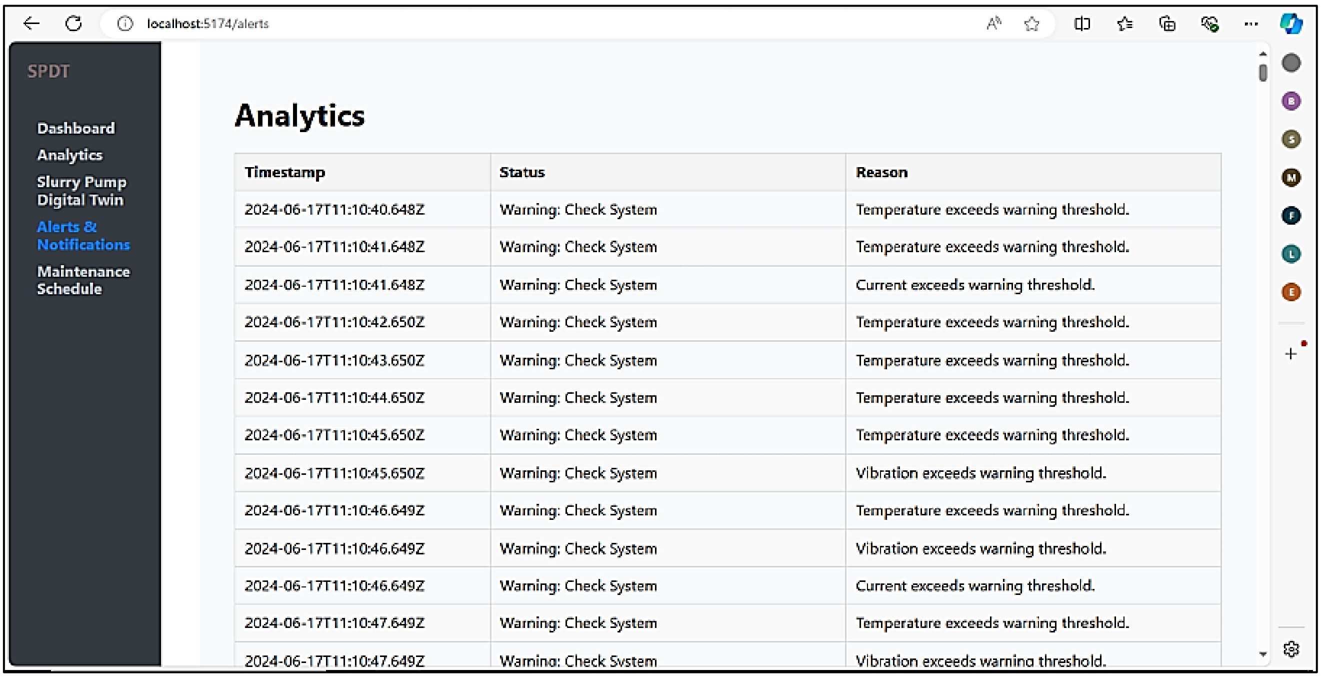


Figure 13 Real-time pump monitoring at critical pump motor vibration warning

4.6.2. Alerts and Notifications Logging

Data from real-time monitoring was captured and stored on the system dashboard, as illustrated in Fig. 14. The stored data was then used to analyse and track pump health and future behaviour.



Timestamp	Status	Reason
2024-06-17T11:10:40.648Z	Warning: Check System	Temperature exceeds warning threshold.
2024-06-17T11:10:41.648Z	Warning: Check System	Temperature exceeds warning threshold.
2024-06-17T11:10:41.648Z	Warning: Check System	Current exceeds warning threshold.
2024-06-17T11:10:42.650Z	Warning: Check System	Temperature exceeds warning threshold.
2024-06-17T11:10:43.650Z	Warning: Check System	Temperature exceeds warning threshold.
2024-06-17T11:10:44.650Z	Warning: Check System	Temperature exceeds warning threshold.
2024-06-17T11:10:45.650Z	Warning: Check System	Temperature exceeds warning threshold.
2024-06-17T11:10:45.650Z	Warning: Check System	Vibration exceeds warning threshold.
2024-06-17T11:10:46.649Z	Warning: Check System	Temperature exceeds warning threshold.
2024-06-17T11:10:46.649Z	Warning: Check System	Vibration exceeds warning threshold.
2024-06-17T11:10:46.649Z	Warning: Check System	Current exceeds warning threshold.
2024-06-17T11:10:47.649Z	Warning: Check System	Temperature exceeds warning threshold.
2024-06-17T11:10:47.649Z	Warning: Check System	Vibration exceeds warning threshold.

Figure 14 Logging of data on alerts and notifications on pump condition

4.6.3. Feature Alerts Analysis

Using information from warning logs on temperature, vibration, and current, the machine learning model analyses and categorises pump motor conditions, as shown in the bar graph in Fig. 15. The concentration of critical warnings on pump vibration indicates the need for repair or replacement of components in the slurry pump motor.

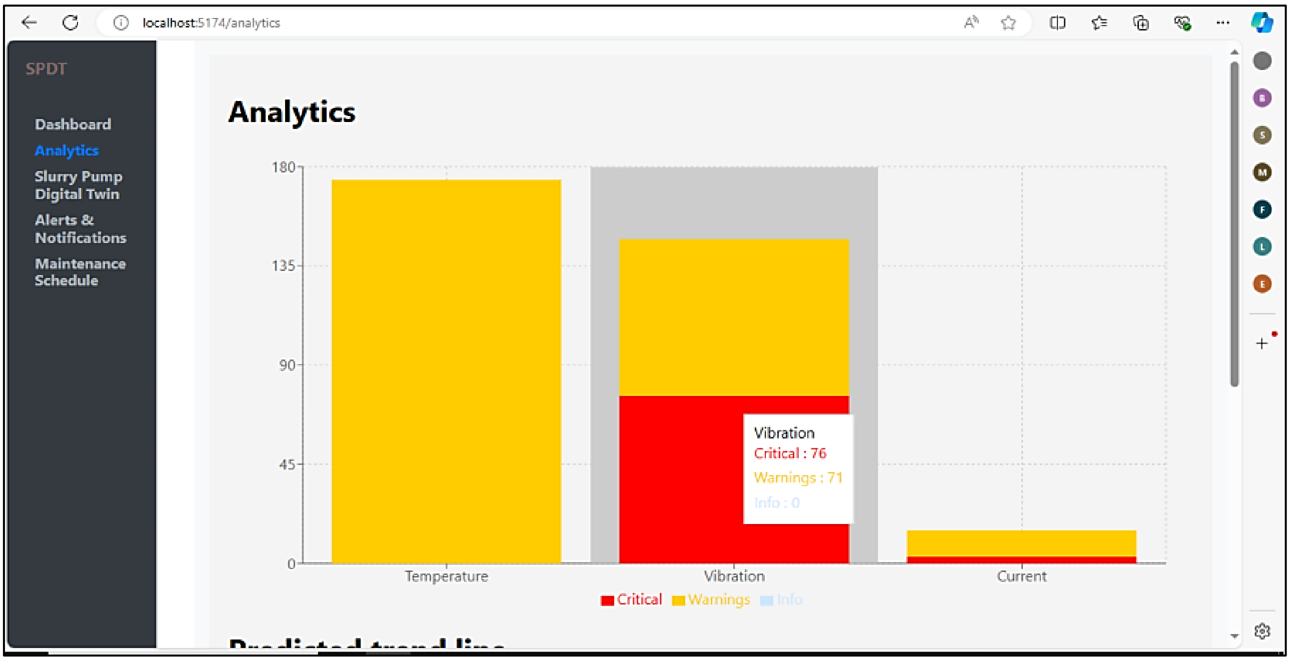


Figure 15 Analysis of slurry pump motor health condition

4.7. Slurry Pump Behaviour Prediction

The predictive analytics of the pump motor health over a month covering temperature, vibration and current are shown in Fig. 16.

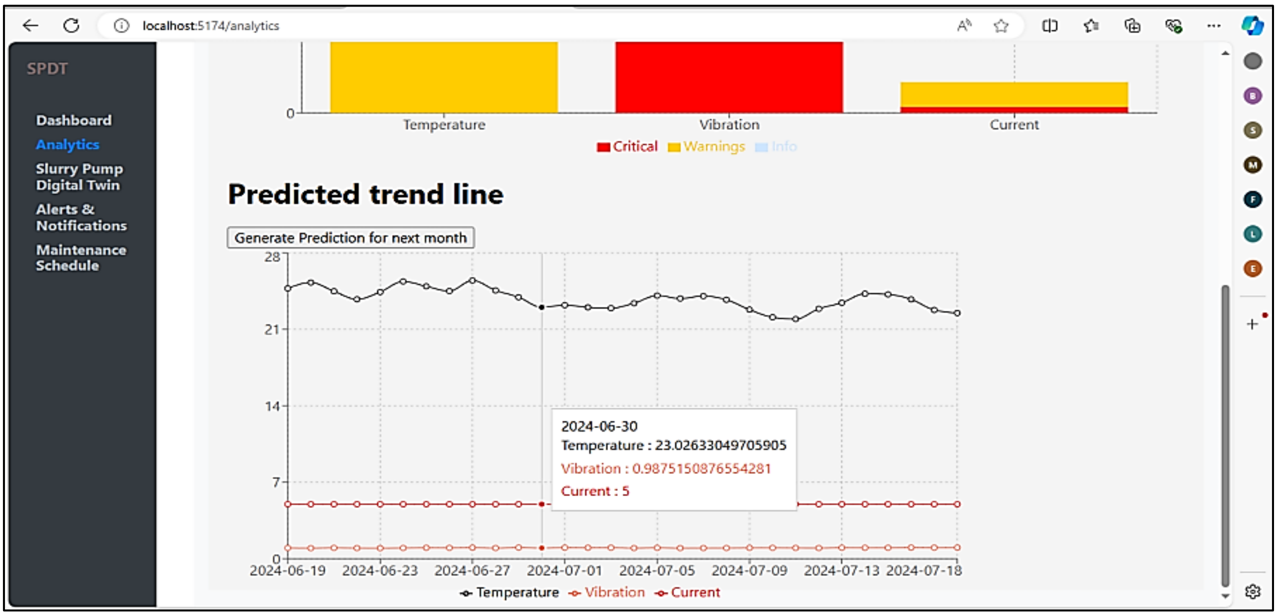


Figure 16 Pump motor health prediction over a month

4.8. Maintenance and Scheduling

After alerts and notifications are analysed by the machine learning model, the final practical step is to schedule the required action, such as repair or replacement. Figure 17 shows how the digital twin system was used to input a maintenance schedule for pump components.

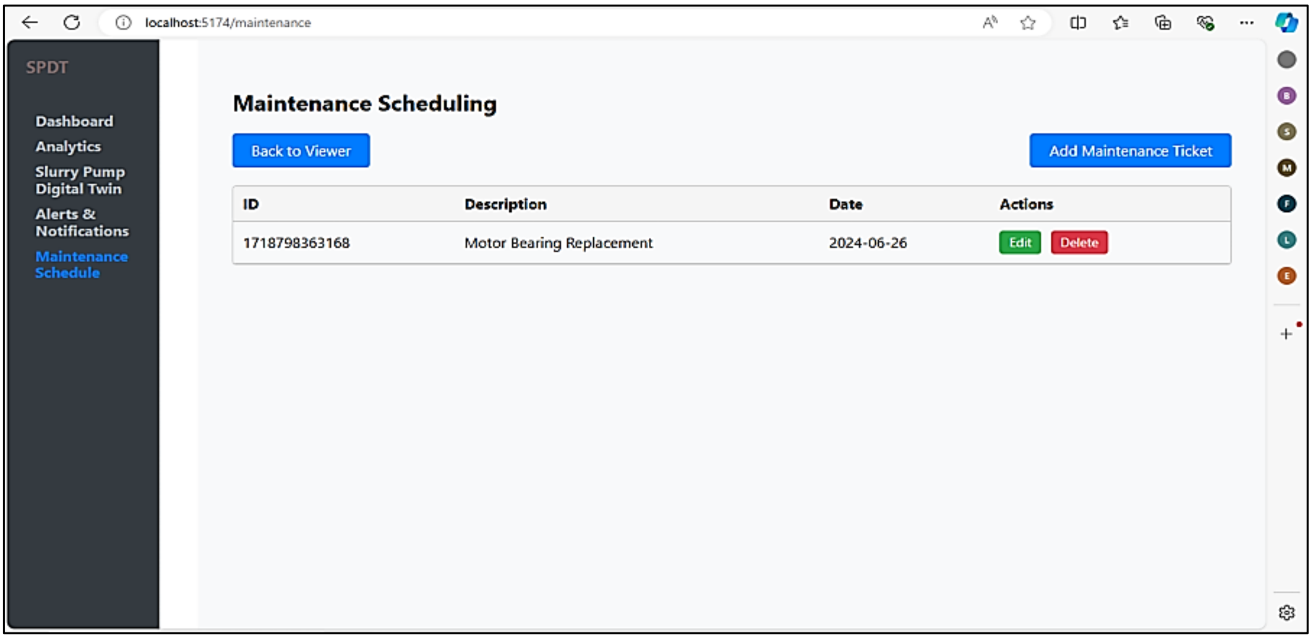


Figure 17 Scheduled maintenance for replacing motor bearing

5. Recommendations

5.1. System Maintenance and Updates

Maintaining the slurry pump digital twin and updating the system to reflect changes in operating conditions are necessary for long-term use. The following maintenance and update actions are recommended:

- Continuously monitor the digital twin's performance and calibrate it as needed.
- Schedule monthly software and hardware updates to ensure that the slurry pump digital twin remains current and accurate.
- Train authorised personnel on proper use of the system so that maximum value can be obtained from the digital twin.
- Develop a data management plan to ensure data integrity and quality.

5.2. Future Work

Further improvements to the slurry pump digital twin were identified to increase system accuracy and optimisation. These are highlighted as follows:

- Include additional sensors and data sources to improve system robustness and accuracy.
- Integrate historical operating and maintenance records into model training to improve machine learning accuracy.
- Extend IoT devices to other plant equipment to support wider plant optimisation.
- Advance monitoring of the pump operating environment and slurry-fluid properties, including density, corrosion, erosive force, and their effects on pump operation.
- Investigate integration of digital twins with other advanced technologies such as augmented reality for improved equipment visualisation and predictive maintenance insights.

6. Conclusion

A slurry pump digital twin was developed on a locally hosted web page using JavaScript in Microsoft Visual Studio Code. The system enabled integration of sensor data from the controller through lightweight communication protocols using specific data fields and topics. An interactive 3D model was connected to real-time data to simulate the physical pump and its operating environment. Machine learning algorithms were trained and validated using data generated on Kaggle, while live and stored sensor data supported diagnosis, alert logging, prediction, and maintenance scheduling.

The model was developed in Google Colab, which provided cloud computational power and storage. The developed prototype demonstrates that a digital twin can be used to perform anomaly detection and diagnose slurry pump faults when suitable sensor data are available. The work therefore provides a practical foundation for predictive maintenance of slurry pumps in mineral processing plants, while future work should focus on additional sensors, higher-quality plant data, and wider integration with existing plant maintenance systems.

Compliance with ethical standards

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Disclosure of conflict of interest

The authors declare that there are no financial or personal relationships that could have inappropriately influenced the research, analysis, or interpretation presented in this paper.

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