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Hybrid Edge-Based Predictive Health Monitoring Model using Statistical Trend and Anomaly Fusion

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Abstract: A lightweight and transparent approach for predicting maintenance of pump systems at the edge is outlined via statistical modeling of time series data, an alternative to other supervised learning techniques that typically require a large labeled data sets (usually tens of thousands) and substantial computational resources. The methodology consists of using Exponential Moving Average, Trend Strength Detection, and Z-score-based anomaly scores to assess the health of pump systems on-line, rather than relying on off-line processing techniques primarily based on deep-learning methodologies. Multi-sensor data including vibration, sound and temperature will be processed in real-time at the edge using a Raspberry Pi computing platform. Exponential Moving Average reduces data noise while retaining and displaying slow degradation trends; Trend Strength Analysis can identify gradual trends in machine health; and the Z-scores serve to quantify deviations from an expected or healthy condition. By combining these outputs into a single Health Index, an easy-to-understand measurement of machine health can be generated. Experimental validation performed under both healthy and simulated degraded conditions demonstrated successful identification of mechanical imbalance, acoustic disturbance and thermal overload. The model will not require the use of supervised learning, therefore providing lower latency, transparency and applicability to lower resourced industrial settings along with offering a cost effective, scalable and less computationally intensive alternative to existing predictive maintenance methodologies.

Keywords: Predictive Maintenance, Edge Computing, Statistical Anomaly Detection, Exponential Moving Average (EMA), Trend Analysis, Industrial Pump Monitoring

I. INTRODUCTION

In water treatment plants, manufacturing facilities, and energy infrastructure, the functioning of industrial pump systems is vital for the continual operation of these businesses. Unforeseen failures of pump systems can create a range of issues; they can cause extended periods of downtime (which costs money), create safety hazards to employees, and create inefficiencies in the overall performance of the plant. The most common forms of maintenance currently used today, reactive maintenance and preventative maintenance, either occur too late to stop a failure from occurring or require unnecessary repair work. Predictive maintenance is an innovative new form of maintenance that uses real-time condition monitoring data to identify equipment that has a high probability of failure before the failure occurs. The Industrial Internet of Things (IIoT) and edge computing have improved how we monitor data from sources, allowing us to monitor performance continuously. However, a lot of existing predictive maintenance models rely on computationally expensive deep learning models and large labeled datasets, thus rendering them impractical for use on low-resource embedded platforms. In addition to this, many methods lack the ability to interpret results and, therefore, their potential for deployment in industrial applications is limited. In order to address these issues, we propose a lightweight statistical ‘edge-based’ predictive maintenance framework which uses Exponential Moving Average (EMA), trend strength detection and Z-score-based anomaly scoring. Through these techniques of smoothing, trend analysis and statistical deviation analysis, this method provides near real-time, explainable fault detection with little processing power. The framework operates entirely on the edge, which ensures low-latency and scalability and is feasible for use with limited resource industrial environments.

II. LITERATURE SURVEY

Literature on predictive maintenance for industrial pump systems has included cloud-augmented analytics, supervised-based machine learning, vibration feature extraction, proposed frameworks in IoT-based telemetry systems, and explainable-based machine learning. Although these works have indicated improved prediction accuracy in terms of fault detection, these works also indicate particular limitations that often rely on labeled datasets, have limitations related to

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real-time processing, and are often rigid in terms of adapting to changing industrial operation and monitoring demands. Accordingly, the existing need for an edge-intelligent, multi-sensor-based, adaptive, and explainable intelligent system for predictive maintenance remains.

Deepan et al. [2025] proposed an AI-powered predictive maintenance framework for industrial IOT environments, focusing on cloud-assisted analytics and supervised learning techniques. Their system outperforms fault detection accuracy but relies heavily on labeled datasets and centralized processing that constrains real-time responsiveness and feasibility of edge deployment. Moreover, the approach does not explicitly provide explainability mechanisms of fault reasoning, which makes it less effective in safety-critical industrial applications.

Zhang et al. [2025] investigated using the feature extraction of vibration energy and frequency domain analysis. This study tends to show the efficacy of vibration energy features in detecting the faults in hydraulic pumps, nevertheless, the approach relies on pre-defined thresholds of the signal and does not dynamically change the response to operational variations. This could trigger false alarms in practical applications.

Li et al. [2025] have proposed the concept of random forest- based fault detection in the case of tunnel drainage pumps, based on the operational data itself. Despite the effectiveness in terms of accuracy, the method is fundamentally supervised, requiring a substantial amount of data related to faults. Additionally, the non-temporal prediction prohibits the method from being used for fault detection.

Ribiero et al. [2024] studied LIME (Local Interpretable Model Agnostic Explanation), SHAP (Shapley Additive exPlanation), PDP (Partial Dependence Plot), and ICE (Individual Conditional Expectation) methods applied for diagnosing rotating machinery faults. Even though this work highlights the interesting aspects of model interpretability, this framework largely supports the offline analysis tasks and lacks real-time sensor fusion processing and real-time anomaly detection at the edge. Moreover, computational costs of explanation tools hinder their use in low-power embedded systems.

Mohiuddin et al. [2024] proposed an IoT-based smart irrigation and monitoring system for efficient water pump operation using various environmental sensors and microcontrollers. This helps in efficient water management. However, the proposed method only deals with irrigation management and does not incorporate predictive maintenance of water pumps.

Wang et al. [2024] proposed multi-physical parameter monitoring where vibration, temperature, and pressure data were used for fault analysis of a pumped storage power generating unit. This work shows the effectiveness of sensor data fusion for fault analysis, but the approach lacks the edge intelligence and normalization.

Huque et al. [2023] proposed an IoT-based water tank monitoring and pump control system. This system utilizes sensors for controlling water pump operation. The proposed system enhances the efficiency of water management. However, it mainly focuses on pump control systems and does not include predictive fault detection. In addition, the proposed research utilizes multiple sensors and statistical anomaly detection to perform predictive maintenance of pump systems.
Calderon et al. [2020] designed a PLC-based monitoring and automation system for water pumping in water treatment plants using wireless sensors. The proposed system facilitates the automatic control of pumps according to water level in the tank. However, it lacks predictive maintenance features, multi-sensor monitoring, and intelligent fault diagnosis.

Sodhro et al. [2019] have proposed an artificial intelligence-based framework to improve edge computing for IIoT applications to process data quickly and avoid cloud computing. However, the paper primarily deals with edge computing architecture and does not discuss predictive maintenance for pump systems or multi-sensor-based condition monitoring. Moreover, health index modeling and real-time explainable fault diagnosis for embedded systems are also missing in this paper.

R. Bayindir et al. [2011] presented an automatic water pumping control system using a programmable logic controller for automatic control of water pump systems depending on water level measurements. This system has contributed to automation and better efficiency, but it is mainly concerned with rule-based systems and does not include predictive fault detection. It does not include multi-sensor condition monitoring for fault detection. In this regard, the proposed research has included a predictive maintenance model using multi-sensor data and statistical models for fault detection and continuous condition monitoring of the pump system.

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In this research, the shortcomings of existing predictive maintenance solutions are overcome by focusing on the shortcomings in cloud dependency, supervised learning, and fixed threshold techniques. The existing literature has not addressed real-time adaptability, dynamic normalization, and multi-sensor fusion for edge implementation. Moreover, interpretability is either non-existent or computationally expensive for edge devices. Thus, there is a need for an edge-intelligent, adaptive, and computationally efficient predictive maintenance solution that can perform continuous health monitoring under different industrial operating conditions.

III. EXPERIMENTAL DETAILS

The experimental validation of the proposed predictive maintenance framework used a Raspberry Pi 5 as the main edge computing unit. The Raspberry Pi 5 was chosen for its strong processing ability, multi-core design, low power use, and support for communication protocols like I2C and 1-Wire. It handles real-time data collection, signal processing, statistical modeling, Health Index calculation, and communication with the time-series database without depending on external cloud services.

To gather a wide range of machine condition data, a multi-sensor setup was used. Vibration monitoring was done with the ADXL345 three-axis digital accelerometer, which communicates over the I2C protocol and provides high-resolution acceleration data. This sensor can detect mechanical issues such as imbalance, misalignment, and bearing wear by tracking changes in vibration amplitude. For acoustic analysis, a MAX4466 microphone module captured high-frequency sounds related to cavitation and structural looseness. Since the Raspberry Pi cannot read analog signals, we added an ADS1115 16-bit analog-to-digital converter (ADC) to convert the acoustic signal through I2C communication. This setup provides high sampling accuracy and sensitivity to noise. We used the DS18B20 digital temperature sensor for temperature monitoring, connecting it through the 1-Wire protocol. A pull-up resistor helped keep the communication stable and the thermal measurements accurate. Temperature data helps identify gradual overheating and wear caused by friction. All sensors were sampled continuously at fixed time intervals, designed for real-time monitoring while keeping computational demands low. The integration of multiple sensors allows for thorough condition assessment by capturing mechanical, acoustic, and thermal features of the pump system in a single edge-based setup.

Figure 1 shows the overall block diagram of Hybrid Edge-Based Predictive Health Monitoring

The block diagram shows the step-by-step workflow of the proposed edge-based predictive maintenance framework. It starts with real-time sensor data collection and ends with generating intelligent alerts. First, multi-modal sensor data from vibration, acoustic, and temperature sensors are continuously collected and divided into fixed time windows. Relevant statistical features are extracted from each window. This helps reduce signal size while keeping important information about the condition. These features go through normalization to make sure that changes in operating conditions do not affect how well we can detect anomalies. The normalized data are then processed with Exponential Moving Average (EMA) smoothing to remove high-frequency noise. After that, we detect trend strength to find gradual degradation patterns. Next, a Z-score-based anomaly scoring system checks for unusual statistical deviations from a healthy baseline. The anomaly scores from various sensors are combined to create a Health Index that shows the overall condition of the machine. The calculated metrics are saved in InfluxDB as timestamped time-series data for tracking and analysis over time. Finally, Node-RED retrieves the processed values to display in a real-time dashboard. Predefined thresholds will trigger warnings or fault alerts if abnormal operating conditions are found. This organized process ensures systematic data handling, clear anomaly detection, and real-time decision support at the edge.

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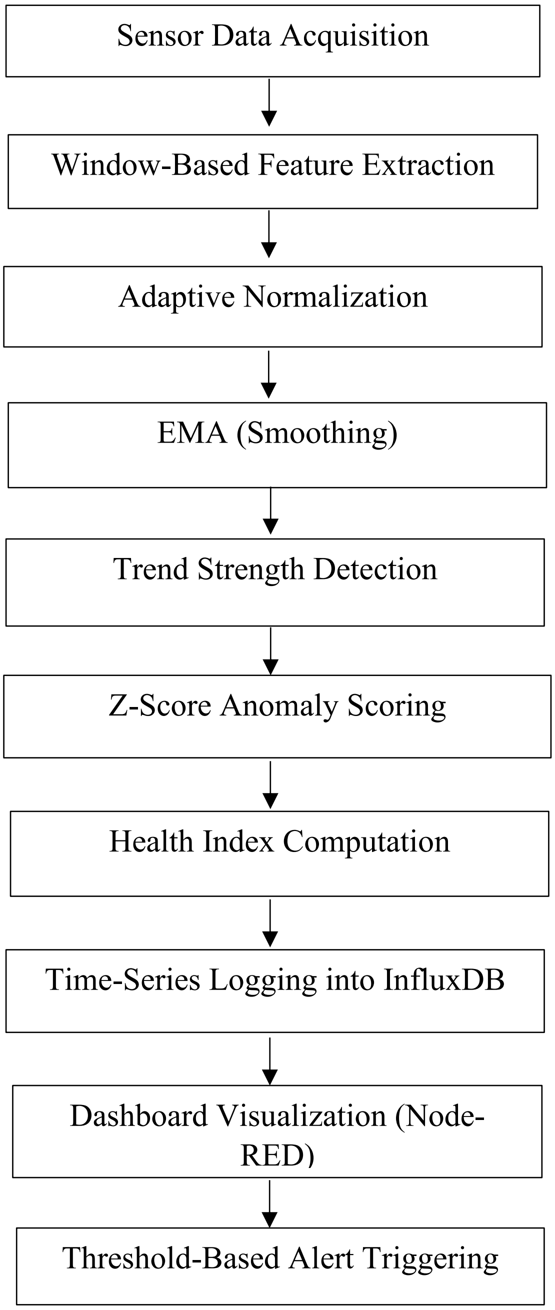

Figure 1: Overall block diagram of predictive maintenance system

The sensor signals from vibration (ADXL345), acoustic emission (MAX4466 with ADS1115), and temperature (DS18B20) were continuously collected in real time using the Raspberry Pi 5 edge platform. Figure 2 represents the sensor output and pump health in raspberry pi terminal.

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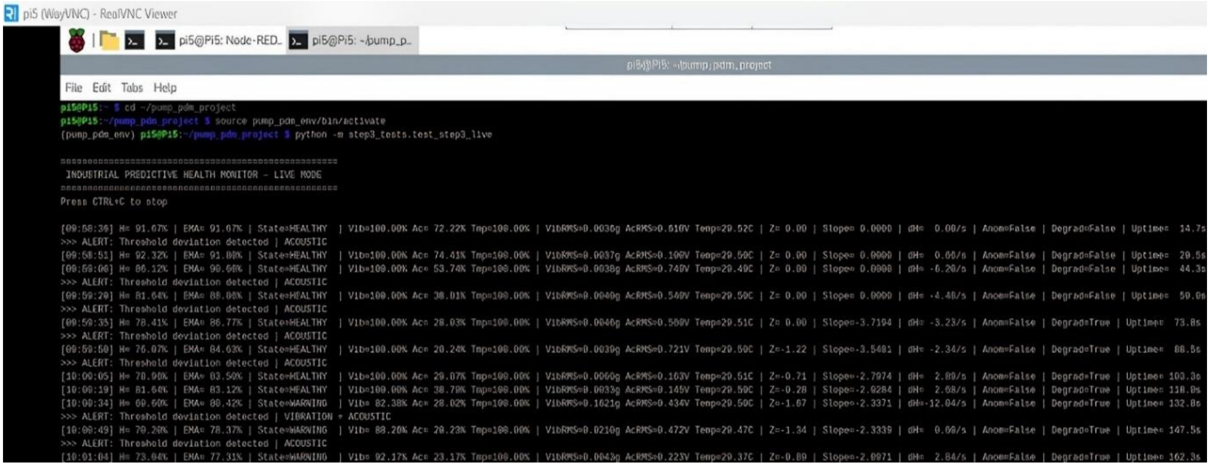

Figure 2: Sensor output and pump health in Raspberry pi terminal

Each sensor was sampled at fixed intervals to maintain steady temporal resolution and synchronized multi-sensor analysis. Since raw sensor streams are high-frequency and may contain noise, analyzing them directly could cause unstable anomaly detection. Therefore, we used a window-based processing method to create structured and meaningful representations of the signals. The continuous data stream was divided into overlapping sliding windows of fixed duration. Each window reflects a short operational period of the pump system, allowing for localized condition assessment. For every window, we extracted statistical features to lower dimensionality while keeping important condition-sensitive information. For vibration signals, we calculated the Root Mean Square (RMS) value to measure signal energy and mechanical intensity. For acoustic data, we determined the average amplitude or energy level to identify unusual sound patterns. For temperature, we used the mean value within the window to represent thermal conditions. These extracted features provide clear and stable indicators of machine behaviour. Next, we processed the feature sequences using Exponential Moving Average (EMA) smoothisng to minimize short-term fluctuations and measurement noise. We selected the smoothing factor (α) based on experimental observations to balance the response to sudden changes with stability during normal operation. A higher α makes the system more sensitive to recent changes, while a lower α focuses on stability. In this study, we chose α to ensure early detection of degradation without causing too many false alarms. To identify gradual degradation, we computed trend strength over consecutive sliding windows by analyzing the rate of change of smoothed features. This approach helps detect progressive mechanical imbalance, increases in acoustic signals, or rises in temperature. We also derived baseline statistical parameters such as mean (μ) and standard deviation (σ) from healthy operating data. We used these baseline values for Z-score calculations, allowing us to evaluate each new feature value against normal operating conditions. This structured acquisition and windowing method ensures reliable statistical modeling and improves the effectiveness of real-time anomaly detection at the edge. Under healthy operating conditions, the pump system remained stable with no disturbances. Sensor readings from vibration, acoustic, and temperature modules stayed within normal limits. The vibration RMS values showed little variation, acoustic amplitude remained steady without unusual spikes, and temperature readings were consistent. This data helped establish baseline statistical parameters, such as mean (μ) and standard deviation (σ), needed for Z-score calculations. This phase also allowed for calibration of the EMA smoothing factor (α) and confirmed the system's stability without false alarms. The Health Index during this period stayed high, indicating normal machine behavior. To simulate mechanical imbalance or shaft misalignment, the vibration amplitude was intentionally increased. This aimed to test how sensitive the proposed framework is to mechanical faults. The rise in vibration energy led to higher RMS values within sliding windows. EMA smoothing tracked the growing vibration intensity while filtering out temporary noise. Trend strength detection noticed a sustained upward trend, suggesting ongoing degradation. At the same time, the Z-score anomaly measure rose as vibration values strayed significantly from the healthy baseline. The Health Index gradually dropped, showing the framework's ability to detect mechanical issues before reaching critical failure points. In this scenario, we introduced external acoustic disturbances to mimic cavitation-like effects or structural looseness. Acoustic signals displayed sudden amplitude spikes and greater variability. The EMA model smoothed out high-frequency fluctuations while still recognizing unusual acoustic energy levels. Unlike gradual vibration changes, this scenario primarily tested the system's reaction to abrupt deviations. The Z-score anomaly score showed quick increases during noise injection events, proving that the system effectively detects deviations. This experiment confirmed the framework's ability to distinguish sudden anomalies from typical operational variations. To simulate overheating conditions, such as bearing friction or lubrication failure, the temperature was gradually raised over time. In contrast to acoustic disturbances, this degradation was slow and steady. The sliding window mean temperature values showed a constant upward trend. EMA smoothing highlighted this rising pattern while keeping stability against minor fluctuations. Trend strength detection effectively identified

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gradual temperature increases, which might not instantly trigger high Z-score values. As the temperature continued to rise beyond baseline levels, anomaly scores increased steadily, and the Health Index dropped correspondingly. This scenario confirmed the system's ability to detect slowly developing faults, which are crucial for predictive maintenance applications. The proposed edge-based predictive maintenance framework was evaluated using various criteria to assess its robustness, sensitivity, reliability, and real-time performance. These parameters help ensure that the statistical modeling approach works well under both normal and abnormal conditions. The first criterion looked at system stability during normal pump operation. Under healthy conditions, the vibration RMS, acoustic amplitude, and temperature values were expected to stay within baseline statistical limits. The EMA smoothing module was tested for its ability to produce steady outputs without amplifying minor noise. Similarly, Z-score anomaly values were expected to remain within acceptable ranges to avoid false positive alerts. A consistently high Health Index during this phase confirmed the framework's reliability and resistance to noise. The second criterion assessed the system's ability to detect gradual changes, such as mechanical wear or thermal buildup. We specifically evaluated how well the system identified gradual increases in vibration or temperature over sliding windows. We monitored the responsiveness of EMA smoothing and the incremental rise in Z-score values to ensure early detection of faults. A gradual decline in the Health Index showed effective tracking of degradation without sudden misclassifications. The third criterion evaluated the framework's response to sudden abnormal events, like acoustic spikes or rapid vibration changes. We tested the Z-score anomaly scoring mechanism for its ability to produce immediate alerts when sensor readings exceeded statistical thresholds. We analyzed the system's detection speed and the magnitude of anomalies to confirm quick identification of faults. This validated the system's effectiveness in dealing with high-impact, short-duration disturbances. We also analyzed the computed Health Index (HI) under all operating scenarios. A stable HI near one during normal operation, a gradual decline during progressive degradation, and a sharp drop during severe anomalies were expected. We examined the smoothness, interpretability, and responsiveness of the HI curve to ensure it provides an intuitive view of machine condition rather than simple fault classification. Finally, we evaluated the system's ability to generate real-time alerts. We set predefined limits for anomaly scores and Health Index values within Node-RED. Figure 3 shows the Node RED visualizatuon.

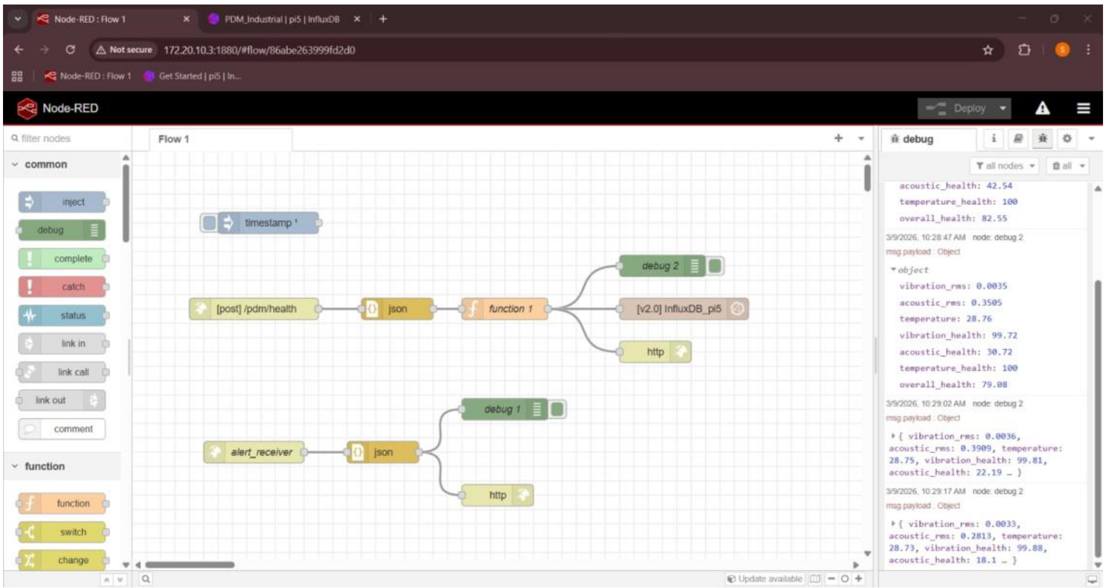

Figure 3: Node RED Visualization

We analyzed how timely and consistently alerts activated during degradation or anomaly scenarios. Successful triggering of warning and fault notifications demonstrated the real-world usability of the framework for industrial monitoring. Throughout the experiments, we continuously timestamped and logged all sensor readings, anomaly scores, and Health Index values into InfluxDB. We visualized the time-series data using Node-RED dashboards to enable trend analysis, performance verification, and validation of alert generation behavior. This evaluation confirmed the reliability, responsiveness, and suitability of the proposed statistical predictive maintenance system for edge applications.

IV. RESULTS AND DISCUSSION

The experimental results show that the proposed lightweight statistical predictive maintenance framework can effectively detect stable operation, gradual degradation, and sudden anomalies. It does this by using EMA smoothing, trend strength

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detection, and Z-score-based anomaly scoring. Under healthy operating conditions, vibration RMS, acoustic amplitude, and temperature readings stayed within baseline limits. The Health Index (HI) consistently remained close to its maximum value, confirming system stability and reducing false alarms. During simulated vibration increases and thermal stress conditions, the framework successfully identified progressive degradation. It did this through sustained positive trend strength and gradually rising Z-score values. This led to a smooth and clear decline in the Health Index instead of sudden fault classification. In scenarios with acoustic disturbances, sudden spikes in amplitude caused immediate Z-score changes and a rapid drop in HI. This showed effective detection of high-impact anomalies. Continuous time-series logging in InfluxDB allowed for clear visualization of degradation trends. Meanwhile, Node-RED dashboards triggered threshold-based warnings and fault alerts in real time. The computational efficiency of the statistical models ensured low processing requirements on the Raspberry Pi edge platform. This validated the framework's suitability for real-time industrial use without depending on cloud-based or resource-heavy deep learning methods. Figure 4 shows the vibration status in Influx DB

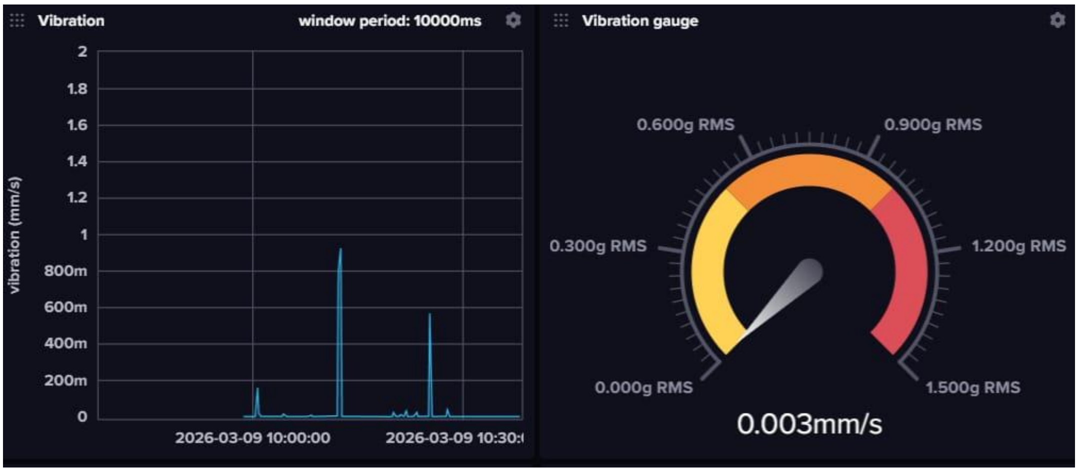

Figure 4: Vibration status in InfluxDB

Figure above shows the vibration monitoring dashboard used in the predictive maintenance system. The graph shows the variation of the vibration levels over time, enabling the user to see changes occurring in the pump condition. The vibration gauge gives a real-time display of the value of the RMS value of the vibration as detected by the accelerometer. This display will help identify unusual patterns of vibration, which might indicate a fault occurring in the pump system. Figure 5 shows the temperature status in Influx DB.

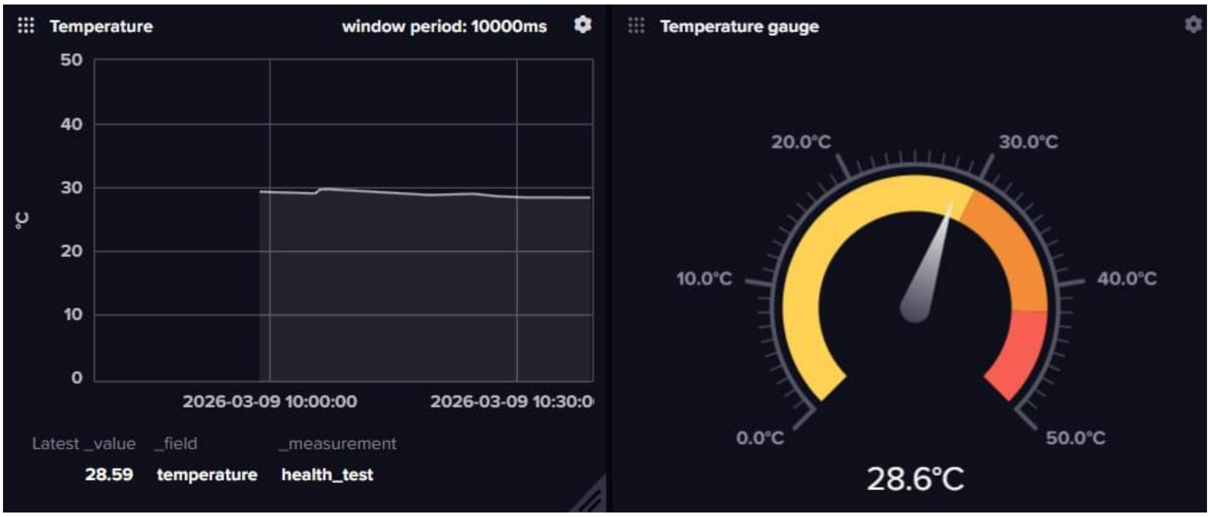

Figure 5: Temperature status in Influx DB

The above figure represents the temperature monitoring dashboard of the predictive maintenance system. The temperature values are shown in the above graph; the change in temperature values is depicted. The temperature gauge represents the temperature of the system at a given point of time; it is detected using the DS18B20 temperature sensor. Temperature values are monitored to detect overheating of the system. Figure 6 shows the Acoustic status in Influx DB.

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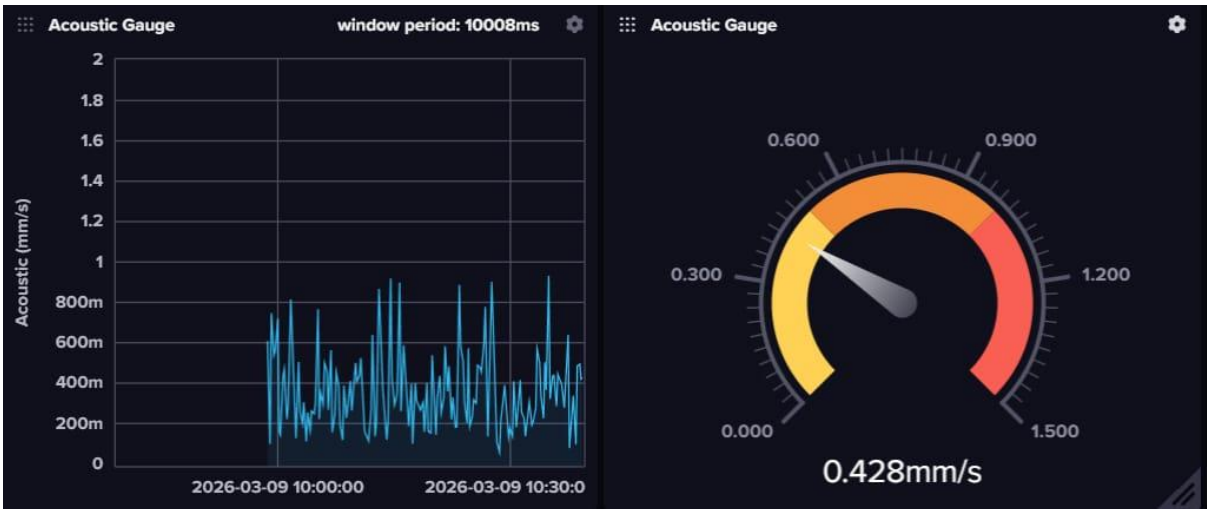

Figure 6: Acoustic status in Influx DB

The above figure represents the overall health monitoring dashboard for the pump system. The graph represents the variation in the calculated Health Index over time, which reflects the overall health status of the pump system. The health gauge represents the overall health status of the pump system in real time. The value on the gauge reflects the overall health status of the system. Higher values on the gauge represent improved health status. Figure 7 shows the threshold alert and check status.

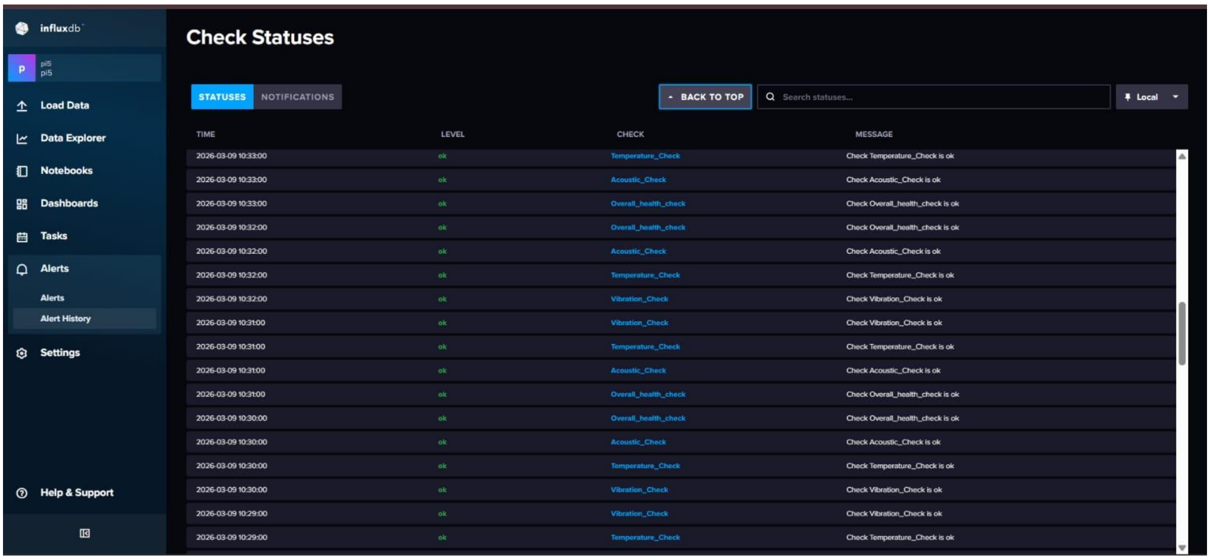

Figure 7: Threshold alert and check status

The image depicts a system status monitoring interface in the InfluxDB dashboard displaying the status for monitored parameters such as Vibration, Acoustic, Temp, and overall health for the pump system. Each indicator displays whether that particular monitored parameter is operating in its normal range. This allows users to confirm pump system performance as well as easily recognize anomaly conditions within the monitoring system.

V. CONCLUSION

This study introduced a lightweight, explainable, and edge-deployable predictive maintenance framework for industrial pump systems using statistical time-series modeling techniques. The approach combines Exponential Moving Average (EMA), Trend Strength Detection, and Z-score-based anomaly scoring. This allows for reliable real-time monitoring of conditions without depending on complex deep learning models or large labeled datasets. The framework was implemented on a Raspberry Pi edge platform and tested in various operating conditions, including normal operation, increased vibration simulations, acoustic disturbances, and thermal stress situations. Experimental results showed that the EMA module effectively reduced high-frequency noise while maintaining important degradation trends, ensuring

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stable performance in normal conditions. Trend strength detection successfully spotted gradual deterioration patterns, allowing early fault prediction instead of reactive detection. The Z-score anomaly scoring provided a clear measure of deviation from healthy behavior, enabling quick identification of sudden anomalies. The Health Index offered a continuous, understandable view of machine condition, improving transparency and supporting better maintenance decisions compared to traditional binary systems. The integration of InfluxDB for time-series logging and Node-RED for real-time visualization further improved the system's usefulness. This setup allows for historical trend analysis and automated alert generation. The low computational load observed during testing confirms that the framework is suitable for embedded industrial settings with limited resources. Overall, this statistical edge-based method offers a scalable, cost-effective, and interpretable alternative to predictive maintenance systems that rely on deep learning. Future work will focus on real-world validation, optimizing adaptive thresholds, and expanding the framework to estimate remaining useful life for better prognostic capabilities.

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