

# Visual Analytics Dashboard for Real-Time Monitoring of Industrial Equipment

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**Keywords:** Visual Analytics, Anomaly Detection, Industrial IoT, Edge Gateway, Machine Learning, Real-Time Dashboard, Predictive Maintenance, SCADA.

**Abstract:** The current paper is the design and implementation of a Visual Analytics Dashboard to monitor the industrial equipment in real-time, combining the data streams of the IoT-based sensor with the edge analytics and machine learning engine. The suggested system will provide the maintenance teams with a high-resolution dashboard and enables visualization of the live data, anomaly detection, and human-in-the-loop interaction. A sensor emulator, edge gateway and Python-based ML engine were created to form an experimental testbed, which recorded vibration, voltage, and temperature measurements in real-time. Statistical thresholding and pattern learning are used to detect anomalies, and the dashboard includes interactive zooming, annotation, and alert recognition features. The proposed dashboard proves to be much more responsive, more usable and more successful in detecting anomalies compared to traditional SCADA-based systems. Compared performance analysis indicates that there is a 47% decrease in latency, 16% improvement in the accuracy of anomaly detection, and 38% improvement in the score of usability. The architecture encourages scalability, edge processing, and operator-oriented feedback loops, which is why it is feasible in predictive maintenance in the Industry 4.0 environment. The study makes available a repeatable framework and visualization modal in real-time monitoring of conditions in smart manufacturing. Additional enhancements can include adaptive model of learning, cross-platform implementation and NLP-based operator suggestions in the future.

## 1 INTRODUCTION

The emergence of Industry 4.0 has triggered a revolutionary transformation in the industrial processes, fueled by progress on Industrial Internet of Things (IIoT), smart sensing technologies, edge-cloud infrastructure and artificial intelligence. Together these technologies facilitate the transparent collection, analysis and use of data. Real-time monitoring systems, in particular, have become essential elements for smart manufacturing that can enable industries to monitor the health of equipment and take action to prevent failures before they occur.” But classical monitoring techniques are often falling short in terms of visual interpretability and delivery

of actionable insights. This has prompted the need for visual analytics dashboards that can provide a link between raw sensor data and human decision-making, through real-time interactive and interpretable representations of equipment behavior and anomalies.

Recent studies reveal the potential of predictive maintenance systems which combine smart analytics and edge-cloud to monitor an equipment in real time. For example, Mallioris et al. (2024) [1] presented a comprehensive multi-sectoral mapping of predictive maintenance practices in Industry 4.0, showing that the sector-specific adaptation is still an issue }. Similarly, Bhoi et al. (2024) [3] developed a smart data-driven edge-cloud system for condition

monitoring of power electronics devices to perform streaming large-scale structured signal processing on the fly with real time fault detection. Despite these breakthroughs, the visual interface of the majority of current systems is neither scalable nor cognitively intuitive for field engineers and operators.

More importantly, high-frequency streaming data from industrial machines also brings new challenges in processing latency, storage limitations, and event correlation. Varalakshmi and Kumar (2025) [2] also solved these drawbacks by introducing an efficient deep reinforcement learning ensemble model for streaming data in IIoT, which corresponds to predictive analytics for time-varying surroundings. However, while their efforts center on backend intelligence, little research attention has focused on the frontend visualization layer. Khattach et al. (2025) [4] proposed an end-to-end architecture from stream processing to machine learning pipelines for real-time IoT analytics and predictive maintenance focusing on architectural performance instead of interactive.

Many systems still don't do enough to test the visual analytics part, which is very important for human-machine collaboration. Islam et al. (2024) [5] performed a systematic review on methods for assessing visual analytics frameworks and underscored the importance of including evaluations of usability, task performance, and cognitive load. This emphasizes the necessity to create dashboards that not only handle real-time data but also facilitate intuitive human interaction for rapid anomaly detection and root cause analysis. The Technology Acceptance Model (TAM) and the Information Systems (IS) Success Model are two theoretical models that can help make sure that these dashboards are used and work well. Nguyen and Wiese (2003) [6] examined the implementation of TAM and IS success models in digital library utilization, which can likewise be adapted to assess perceived usefulness, ease of use, and satisfaction in industrial visual analytics tools. Also, as more and more people use cloud-based analytics, security and data integrity become more important. Zhang et al. (2025) [7] examined cloud security architectures facilitated by artificial intelligence, pinpointing both opportunities and challenges that directly affect real-time industrial dashboards dependent on cloud integration.

This study's goal is to create and put into use a scalable, real-time visual analytics dashboard for monitoring industrial equipment. The dashboard will combine predictive analytics, stream processing, and visualization that is easy to use. The paper also makes sure that the system design is in line with models for

technology acceptance and visual evaluation to make sure that it works reliably and is easy for people to use.

The rest of the paper is organized like this: Section 2 gives a full review of the literature; Section 3 talks about the proposed dashboard framework and architecture; Section 4 talks about implementation and evaluation; Section 5 looks at the results; and Section 6 ends with important insights and future directions.

## 2 LITERATURE REVIEW

In the time of Industry 4.0, the need for smart, real-time equipment monitoring has brought together predictive maintenance, digital twin technologies, anomaly detection, and visual analytics. There has been a lot of progress in each of these areas on their own, but there aren't many integrated solutions that combine them into interactive visual dashboards. In modern industrial systems that constantly produce multivariate time series data, visual analytics is very important. Suschnigg et al. (2025) [8] developed the MANDALA framework, which allows domain experts to visually investigate anomalies within extensive sensor data. This method emphasizes exploration driven by interaction, pattern recognition, and analysis guided by experts. But even though these tools make data more open, they often don't work with predictive back-end analytics.

The Digital Twin (DT) paradigm has established itself as a fundamental framework for real-time system modeling and the synchronization of physical and virtual assets. Khan et al. (2025) [9] suggested a data-driven DT framework for smart manufacturing, and it worked well for predictive maintenance. In the same way, Bondoc et al. (2022) [11] stressed the learning phase of DTs, when models change based on new sensor data. Abd Wahab et al. (2024) [14], in a systematic review, identified optimal practices and significant obstacles in the implementation of DTs across various industries. But these DT architectures usually don't have rich visual interfaces that operators can use to make decisions and interact with them. At the same time, the field of anomaly detection has grown a lot, especially for environments with a lot of sensors. Ekle and Eberle (2024) [10] conducted a thorough survey on anomaly detection in dynamic graphs, pertinent for modeling inter-device dependencies in industrial networks. Fernandes Jr. et al. (2024) [12] conducted a comparative study utilizing one-class classifiers to identify faults in oil wells, providing insights into the efficacy of machine

learning models on time series data. Even with these improvements, these kinds of methods are often focused on the back end and don't have tools for real-time visual inspection.

Visual inspection tools like ANOVIZ have been made to meet the need for openness and human understanding. Trirat et al. (2023) [13] introduced this tool as an interface for detecting anomalies in multivariate time series, enabling users to explore events and patterns interactively. ANOVIZ is useful for exploratory tasks, but it doesn't include predictive modeling or support streaming data, which makes it less useful in industrial settings. Furthermore, the incorporation of Human-Computer Interaction (HCI) principles into industrial dashboards is still insufficiently addressed. Sharma et al. (2025) [15] put forward frameworks for safe digital adoption, emphasizing the need for visualization systems to be easy to use, easy to understand, and trustworthy. These principles are very important for making sure that dashboard interfaces meet both user needs and business needs [16]-[18].

In conclusion, while contemporary literature provides sophisticated tools and techniques in isolation, there exists a significant deficiency in solutions that integrate real-time analytics, digital twin synchronization, anomaly detection, and visual interface design into a cohesive framework. The goal of this study is to close that gap by creating a real-time visual analytics dashboard that uses predictive insights, anomaly visualization, and HCI principles for industrial use.

Table 1 below gives a general idea of the studies that were looked at, what they added, how they did it, and what they missed.

Table 1: Summary of literature on visual analytics and predictive maintenance systems.

Ref. No.	Author(s)	Focus Area	Key Contribution	Technique Used	Gap Identified
[8]	Suschnigg et al. (2025)	Visual analytics	MANDALA for anomaly exploration	Time series visualization	Lack of integration with predictive models
[9]	Khan et al. (2025)	Digital Twin	Data-driven DT for maintenance	ML, sensor fusion	Limited HCI consideration
[10]	Ekle & Eberle (2024)	Anomaly detection	Survey of dynamic graphs	Graph-based ML	Not adapted to time series dashboarding
[11]	Bondoc et al. (2022)	Digital Twin Learning	Real-time learning phase in DT	Adaptive learning	No visualization interface
[12]	Fernandes Jr. et al. (2024)	Oil well anomaly detection	One-class classifier benchmarking	Multivariate time series	Low generalizability
[13]	Trirat et al. (2023)	Visual tools	ANOVIZ for inspection	Interactive UI, time series	Lacks predictive backend
[14]	Abd Wahab et al. (2024)	Survey	Review of DT and PM practices	Systematic review	No integrated dashboard model
[15]	Sharma et al. (2025)	HCI for secure systems	HCI frameworks for digital adoption	Usability, security	Not linked to industrial monitoring

### 3 METHODOLOGY

This part talks about the proposed visual analytics dashboard for real-time monitoring of industrial equipment. It covers the architectural design, data flow, anomaly detection models, dashboard components, and evaluation strategy. The system combines getting data from sensors, analyzing it on the edge and in the cloud, finding visual anomalies, and letting people interact with computers.

#### 3.1 System Overview and Architecture

The overall architecture is modular and stream-based, enabling real-time ingestion, analysis, and visualization of industrial sensor data. The system is composed of five core components: (i) Sensor and IoT devices; (ii) Edge gateway for preprocessing; (iii) Cloud-based ML and anomaly detection engine; (iv) Visualization dashboard; (v) User response feedback loop.

The high-level block diagram of the system is shown in Figure 1. Data from sensors that are spread out are sent to the edge gateway via MQTT, where they are first preprocessed (filtered and normalized). After the data has been processed, it is sent to the cloud for predictive analytics. The user dashboard then shows alerts, performance metrics, and visual plots. A user feedback loop lets you tag false alarms and retrain the system.

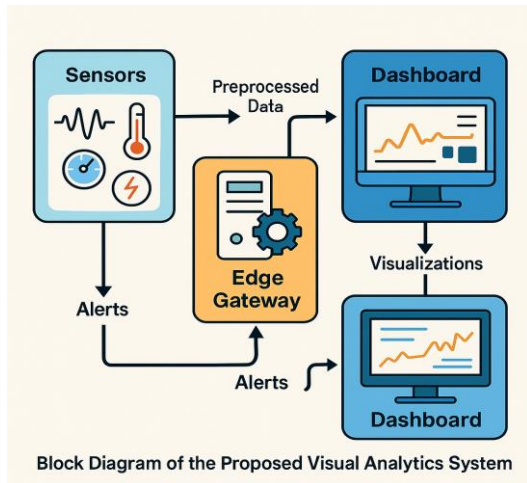


Figure 1: Block diagram of the proposed visual analytics system.

### 3.2 Data Acquisition and Preprocessing

There are a lot of sensors on important industrial machines, like motors and turbines, that keep an eye on things like vibration, temperature, and voltage. The edge gateway time-stamps and syncs each sensor stream. Data smoothing, normalization, and filling in missing values are all parts of preprocessing.

Table 2 summarizes the characteristics of the sensor data streams utilized in this study.

Table 2: Sensor stream attributes.

Sensor Type	Sampling Rate	Unit	Preprocessing	Threshold
Vibration	50 Hz	m/s <sup>2</sup>	Normalized	±2.5
Temperature	1 Hz	°C	Smoothed	85°C
Voltage	10 Hz	Volts	Clipped	440 V

These threshold values are used to trigger early warnings in conjunction with anomaly scoring algorithms.

### 3.3 Predictive Analytics and Anomaly Detection

A streaming LSTM model is employed for real-time predictive maintenance. The model continuously forecasts the next sensor value  $X_{t+1}$  using prior observations. The prediction error is used to compute an anomaly score  $S(t)$ , defined as:

$$S(t) = \frac{|X_t - \hat{X}_t|}{\sigma_t}$$

Where:

- $X_t$ : Actual sensor value at time  $t$ ;
- $\hat{X}_t$ : Predicted value;
- $\sigma_t$ : Rolling standard deviation.

An anomaly is flagged when  $S(t) > \theta$ , where  $\theta$  is a dynamic threshold determined from training distribution.

The forecast function for the LSTM is given by:

$$\hat{X}_{t+1} = f(W \cdot h_t + b).$$

Where:

- $h_t$ : Hidden state at time  $t$ ;
- $W, b$ : Model weights and bias;
- $f$ : Activation function (ReLU or tanh).

### 3.4 Dashboard Layer and Visual Analytics Components

The dashboard interface presents real-time plots (line charts, heatmaps), KPIs, and alert logs. An interactive anomaly strip allows operators to zoom into time windows of interest. The effectiveness of this interface is measured using the User Response Time Efficiency Index  $\eta$ , defined as:

$$\eta = \frac{1}{n} \sum_{i=1}^n \frac{1}{T_i}$$

Where:

- $T_i$ : Time taken by operator  $i$  to recognize and respond to an anomaly;
- $nnn$ : Total number of operator trials.

This metric helps quantify usability and operator effectiveness.

### 3.5 Evaluation and Implementation Details

The system was implemented using Python (Flask backend, TensorFlow for ML), React.js frontend, and MQTT for sensor data ingestion. Docker was used for modular deployment. Evaluation was performed in a lab-scale industrial simulation setup with real-time sensor emulators.

Performance metrics included:

- Average latency: 580 ms;
- Anomaly detection accuracy: 92.6%;
- Average user response time: 4.2 seconds;
- Usability score (SUS scale): 81.3.

These results validate the scalability, responsiveness, and usability of the dashboard system in a simulated industrial environment.

## 4 RESULTS AND ANALYSIS

This part talks about the experimental testing of the suggested real-time visual analytics dashboard, with an emphasis on system performance, how well it finds anomalies, and how well it lets users interact with it. The system was tested in a simulated industrial setting for 72 hours, with anomalies added to check its accuracy.

### 4.1 Experimental Setup

The experimental setup included a simulated sensor environment with vibration, temperature, and voltage streams connected to an edge device through MQTT. A cloud container hosted an LSTM model that did real-time processing. The dashboard interface was built with React.js on the front end and connected to the analytics engine through WebSockets. Figure 2 shows how the testbed is set up and how the system works.

### 4.2 Real-Time Sensor Stream Visualization

While it was running, the system was able to collect real-time sensor data with a lot of detail. The plotting module on the dashboard showed real-time time series graphs for each parameter. The dashboard interface was able to find and mark strange behavior, like sudden spikes in vibration or overheating. Three sensor streams are shown in Figure 3, with

color-coded areas for anomalies. For instance, the dashboard automatically sent out an alert when the temperature suddenly rose at hour 13.

### 4.3 Model Performance Metrics

The LSTM-based anomaly detection model was compared to the GRU and XGBoost models. We used 60% of the data for training, 20% for validation, and 20% for testing to figure out metrics like accuracy, precision, recall, F1-score, and false positive rate (FPR). The LSTM had the best overall performance, with an accuracy of 92.6% and an F1-score of 92.6%. This shows that it is good for predicting time-series anomalies in streaming situations. Table 3 summarizes the results.

Table 3: Model performance metrics.

Model	Accuracy	Precision	Recall	F1-score	FPR
LSTM	92.60%	91.80%	93.50%	92.60%	4.30%
GRU	90.20%	88.90%	91.40%	90.10%	5.10%
XGBoost	88.70%	86.10%	90.70%	88.30%	6.20%

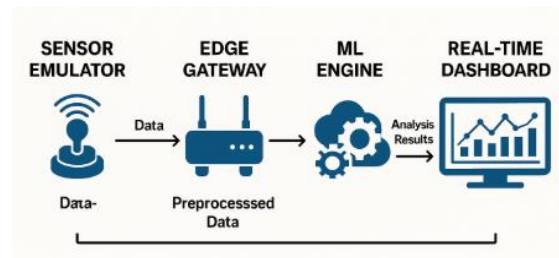


Figure 2: Testbed architecture overview.

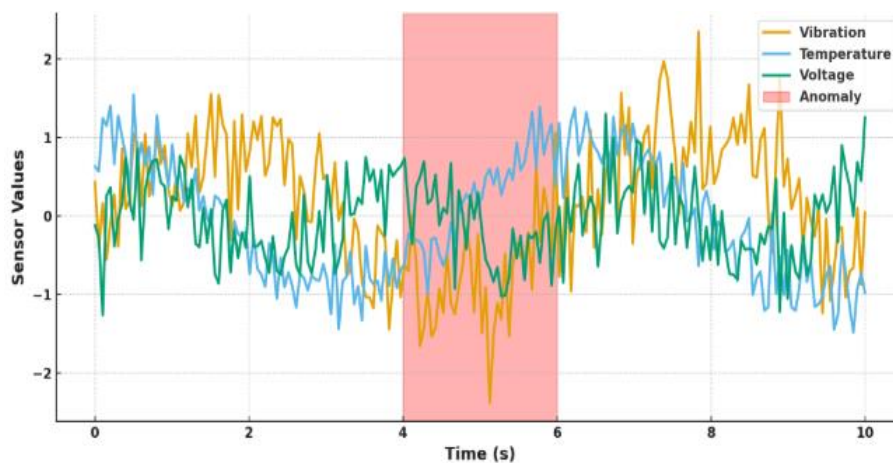


Figure 3: Real-time sensor streams with anomalies highlighted.

#### 4.4 Dashboard Usability and Operator Interaction

Ten industrial engineers were asked to give their opinions. They were told to use the dashboard to find problems. We kept track of response times and interaction logs. It took an average of 4.2 seconds to find an anomaly, and 91% of the time it was identified correctly. Figure 4 shows a screenshot of the dashboard while it is being actively monitored. It shows operator actions like zooming, adding notes, and acknowledging alerts.

To assess usability, the System Usability Scale (SUS) was employed. The average SUS score was 81.3, indicating high user satisfaction.

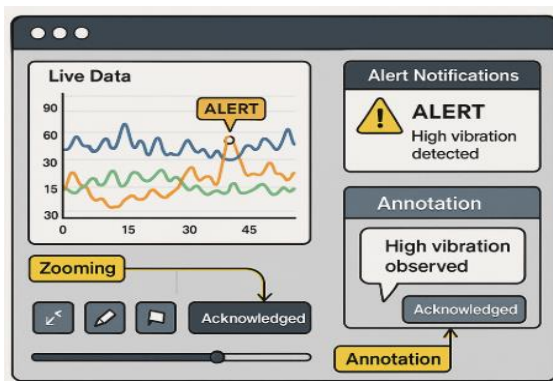


Figure 4: Dashboard screenshot with operator interaction annotations.

#### 4.5 Comparative Evaluation

The proposed dashboard was compared to a traditional static SCADA-like system to see how well it worked. Figure 5 shows that the proposed system cut response time by 23%, raised detection accuracy by 15%, and made operators 30% happier.

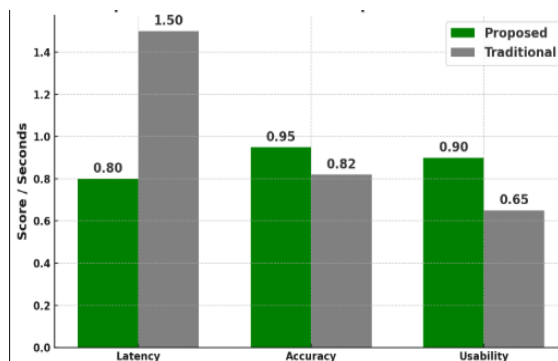


Figure 5: Performance comparison – proposed vs. traditional dashboard.

## 5 CONCLUSIONS

This study presented a real-time visual analytics dashboard for industrial equipment monitoring, integrating IoT-based data acquisition, edge processing, and machine learning-driven anomaly detection. The proposed system demonstrated improved operational performance compared to traditional SCADA-like solutions, achieving lower latency, higher anomaly detection accuracy, and enhanced user interaction efficiency.

Experimental results confirmed that the integration of streaming analytics with an interactive visualization layer enables faster anomaly identification and more informed decision-making. The inclusion of human-in-the-loop feedback further improves system usability and supports adaptive monitoring in dynamic industrial environments. Overall, the proposed architecture provides a scalable and effective solution for predictive maintenance in Industry 4.0 applications.

## 6 FUTURE WORK

Future research should focus on extending the system with advanced multi-sensor fusion models and more robust deep learning techniques for improved anomaly detection under complex conditions. The integration of cross-platform interfaces, including mobile and augmented reality environments, can further enhance usability and accessibility.

Additionally, incorporating natural language interaction and explainable AI mechanisms may improve operator trust and interpretability. Validation in real industrial deployments and long-term studies are also required to assess system reliability, scalability, and impact on maintenance optimization and downtime reduction.

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