

Edge AI Based Anomaly Detection for Real Time Monitoring of IoT Enabled Industrial Systems

Marsutiyawan Aji

¹PT. Karyatama Solusindo

Corresponding Author: Marsutiyawan Aji, aji@karyasolusi.id

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ABSTRACT

Industrial machine failures can reduce productivity and increase maintenance costs, requiring an effective real-time monitoring approach. This study develops an Edge AI-based anomaly detection system for IoT-enabled industrial systems using multi-sensor data consisting of vibration, temperature, and current measurements. The proposed method applies an Autoencoder model deployed on an edge computing device to identify abnormal machine conditions with low latency. The novelty of this study is the integration of lightweight AI inference and multi-sensor analysis for real-time industrial monitoring. Experimental evaluation using 10,000 sensor data samples achieved 96.8% accuracy, 95.9% precision, 96.3% recall, and 96.1% F1-score with a response time of 0.28 seconds. The proposed system supports efficient predictive maintenance applications

INTRODUCTION

The rapid development of Industry 4.0 has accelerated the transformation of conventional manufacturing systems into intelligent, interconnected, and data-driven industrial environments. Modern industrial equipment is increasingly equipped with Internet of Things (IoT)-based sensors capable of continuously collecting operational information, including vibration, temperature, electrical current, and other machine health indicators. This transformation enables industries to move from traditional maintenance strategies toward predictive maintenance approaches that utilize real-time data analysis to anticipate equipment failures. Predictive maintenance has gained significant attention because unexpected machine failures may cause production interruptions, increased operational costs, and reduced system reliability (Carvalho et al., 2019). Furthermore, industrial organizations are increasingly adopting data-driven maintenance strategies because they provide better decision support compared with periodic maintenance approaches that may not accurately represent the actual condition of equipment (Kumar et al., 2020).

The implementation of Industrial Internet of Things (IIoT) provides significant opportunities for improving machine monitoring through continuous data acquisition and automated analysis. Sensor-based monitoring systems allow industrial operators to identify abnormal changes in equipment behavior before severe failures occur. However, the increasing deployment of IoT devices also generates large volumes of heterogeneous data that require efficient processing mechanisms. Conventional cloud-based architectures often transmit all collected data to centralized servers, which may introduce communication delays, bandwidth consumption, and dependency on network availability. Shi et al. (2020) explained that edge computing addresses these limitations by moving computational processes closer to data sources, allowing faster decision-making and reducing communication overhead. This capability is particularly important for industrial applications requiring real-time responses and low-latency monitoring.

Artificial intelligence (AI) has become an essential technology for analyzing complex industrial sensor data and identifying abnormal operational patterns. Unlike conventional threshold-based monitoring methods, AI-based approaches can learn hidden relationships within historical data and detect deviations that may indicate early-stage failures. Deep learning methods have demonstrated strong performance in industrial anomaly detection because they can automatically extract representative features from large-scale sensor datasets. According to Lei et al. (2020), deep learning approaches have shown considerable potential for machinery fault diagnosis by learning complex patterns from vibration and operational signals. Similarly, Autoencoder-based models have been widely applied for anomaly detection because they can reconstruct normal operational patterns and identify abnormal conditions through reconstruction errors (Sakurada & Yairi, 2014; Zhou & Paffenroth, 2017).

Despite significant advances in AI-based industrial monitoring, several challenges remain before these approaches can be effectively implemented in real industrial environments. Many existing studies still rely on centralized cloud-

based processing, where computationally intensive models are executed on remote servers. Although cloud-based approaches provide high computational capacity, they may not satisfy the requirements of industrial systems that demand immediate responses. Kalør et al. (2021) highlighted that resource-constrained industrial IoT devices face challenges related to communication limitations, energy consumption, and computational resources, making edge-based anomaly detection an important research direction. Moreover, several existing studies focus on single sensor modalities, such as vibration signals only, while real industrial machine conditions are generally influenced by multiple physical parameters. Integrating multiple sensor sources can provide a more comprehensive representation of machine health conditions and improve anomaly identification capability.

Recent studies have explored the integration of edge computing and AI to overcome the limitations of conventional industrial monitoring systems. For example, deep learning-based anomaly detection architectures have been developed to support real-time IoT applications by distributing intelligence between edge devices and centralized systems (Savic et al., 2021). Other studies have investigated lightweight AI models to enable deployment on devices with limited computational resources, demonstrating the feasibility of performing intelligent analysis closer to industrial equipment. However, a research gap remains in developing practical Edge AI frameworks that combine lightweight anomaly detection models with multi-sensor industrial data while maintaining detection accuracy and low response latency. Therefore, further investigation is required to develop efficient and deployable solutions for real-time industrial condition monitoring.

Based on these research gaps, this study aims to develop an Edge AI-based anomaly detection framework for real-time monitoring of IoT-enabled industrial systems. The research focuses on utilizing multi-sensor machine condition data, including vibration, temperature, and electrical current parameters, to identify abnormal equipment behavior. Unlike conventional approaches that rely primarily on centralized processing, this study emphasizes local AI inference on edge devices to achieve faster response and more efficient industrial monitoring. The proposed approach is expected to support predictive maintenance implementation by providing early detection of potential equipment failures.

The contribution of this research is twofold. From an academic perspective, this study contributes to the development of Industrial Internet of Things research by investigating the application of lightweight AI-based anomaly detection within edge computing environments. From a practical perspective, the proposed system provides an alternative solution for industries to improve equipment reliability, reduce unplanned downtime, and optimize maintenance decision-making. By integrating IoT sensing capabilities, Edge AI processing, and anomaly detection techniques, this research supports the development of intelligent industrial monitoring systems that are more responsive, efficient, and suitable for real-world deployment.

THEORETICAL REVIEW

Industrial Internet of Things (IIoT) for Machine Condition Monitoring

Industrial Internet of Things (IIoT) has become a fundamental technology in smart manufacturing by enabling the integration of industrial equipment, sensors, communication networks, and data analytics platforms. Through IIoT implementation, industrial machines can continuously generate operational data such as vibration, temperature, current, and pressure, which are essential indicators for evaluating equipment conditions. The availability of real-time sensor data allows industries to shift from conventional preventive maintenance toward predictive maintenance strategies that can identify potential failures before they interrupt production processes. Rakholia et al. (2025) explained that the integration of AI and IoT in manufacturing environments supports predictive maintenance by analyzing machine behavior and predicting possible operational problems before failure occurs.

Sensor-based monitoring systems are particularly important because industrial failures often appear through gradual changes in operational patterns rather than sudden events. Therefore, analyzing multiple sensor parameters can provide a more comprehensive understanding of machine health conditions. Erhan et al. (2020) emphasized that anomaly detection in sensor systems requires efficient information fusion because industrial sensor environments generate high-volume and high-speed data streams with complex relationships between variables. Based on these studies, the utilization of multi-sensor IIoT data becomes an important foundation for developing intelligent anomaly detection systems.

H1: The utilization of multi-sensor industrial IoT data improves the capability of anomaly detection systems in identifying abnormal machine conditions compared with single-parameter monitoring approaches.

Edge AI for Real-Time Industrial Monitoring

Although cloud computing provides powerful computational resources, centralized processing introduces several challenges for industrial applications, particularly regarding latency, network dependency, and data transmission costs. Edge computing addresses these limitations by moving computational processes closer to data sources, allowing faster analysis and real-time decision-making. In industrial environments, this approach is increasingly combined with artificial intelligence, known as Edge AI, to enable intelligent processing directly on local devices.

Recent research has demonstrated that edge-based anomaly detection can improve the efficiency of industrial monitoring systems. Yu et al. (2022) proposed an edge computing-based anomaly detection approach capable of identifying abnormal patterns from both single-source and multi-source sensor time-series data. Their study showed that edge-based processing can improve scalability and reduce dependence on centralized computing infrastructures. Furthermore, recent studies highlight that lightweight AI models are required because industrial edge devices generally have limited memory, processing capability, and energy resources (Reis et al., 2025).

The implementation of Edge AI in industrial monitoring therefore focuses not only on detection accuracy but also on achieving low inference latency and

efficient computational performance. A system that can perform anomaly detection directly at the edge has the potential to provide faster warnings and support real-time maintenance decisions.

H2: Deployment of AI-based anomaly detection models on edge computing devices reduces monitoring response latency while maintaining reliable detection performance for industrial systems.

Deep Learning and Autoencoder-Based Anomaly Detection

Anomaly detection aims to identify operational patterns that significantly deviate from normal system behavior. In industrial applications, anomaly detection is challenging because abnormal events usually occur less frequently than normal operating conditions. Therefore, many recent studies have adopted unsupervised and semi-supervised deep learning approaches that can learn normal operating patterns without requiring large amounts of failure data.

Autoencoder-based models are widely applied for anomaly detection because they learn compact representations of normal data and identify abnormal conditions through reconstruction errors. Deep learning approaches are particularly suitable for industrial sensor data because they can automatically extract complex features from multidimensional time-series signals. Adhikari et al. (2024) reviewed recent developments in IoT anomaly detection and highlighted that deep learning methods provide strong capability for detecting complex abnormal patterns in large-scale sensor environments.

For industrial applications, the combination of Autoencoder models with IoT sensor data provides an effective approach for identifying early-stage machine degradation. Chevtchenko et al. (2023) conducted a systematic mapping study on anomaly detection in industrial machinery using IoT devices and machine learning, showing that vibration-based monitoring, sensor fusion, and machine learning algorithms are among the dominant approaches for industrial fault detection. However, many existing studies still focus primarily on algorithm performance without considering deployment limitations on edge devices.

Previous Studies and Research Gap

Previous studies have demonstrated the effectiveness of AI-based anomaly detection in industrial environments. Yu et al. (2022) developed an edge computing-based anomaly detection algorithm that considered correlations among multi-source time-series sensor data, addressing limitations of traditional single-source anomaly detection methods. However, the study focused mainly on anomaly detection algorithms and did not extensively investigate lightweight AI deployment on constrained edge hardware.

Similarly, Reis et al. (2025) proposed a lightweight anomaly detection framework combining signal processing techniques and edge-deployed machine learning models for IoT sensor networks. The research demonstrated that efficient feature processing and lightweight models can reduce latency and computational requirements. Nevertheless, further research is required to integrate lightweight AI inference with industrial machine monitoring using multiple operational parameters.

Recent surveys also indicate that industrial anomaly detection research still faces challenges related to real-time implementation, computational efficiency, and adaptation to practical industrial environments. Li et al. (2025) reported that although deep learning has significantly improved anomaly detection performance, deployment challenges remain due to model complexity and requirements for reliable industrial operation. Therefore, this research positions itself by developing an Edge AI-based anomaly detection framework that combines multi-sensor industrial data, lightweight AI processing, and real-time monitoring capabilities.

METHODOLOGY

Research Design and Sample Characteristics

This study employed a quantitative experimental research design to develop and evaluate an Edge AI-based anomaly detection framework for real-time monitoring of IoT-enabled industrial systems. The research focused on developing an intelligent monitoring approach capable of identifying abnormal machine conditions based on operational sensor patterns. An experimental design was selected because the research aimed to measure the performance of the proposed AI model objectively through quantitative evaluation indicators, including detection accuracy, classification performance, and response latency.

The research sample consisted of industrial machine operational data collected from IoT-based monitoring sensors. A total of 10,000 sensor observations were analyzed, consisting of three main parameters: vibration, temperature, and electrical current. These parameters were selected because they represent important indicators of industrial equipment health. Vibration reflects mechanical changes caused by imbalance or component degradation, temperature indicates thermal changes during operation, and electrical current represents variations in machine workload. Previous studies have demonstrated that combining multiple sensor parameters can provide a more comprehensive representation of machine conditions compared with single-sensor monitoring approaches (Chevtchenko et al., 2023).

The dataset was categorized into two operational conditions: normal and abnormal conditions. The dataset distribution consisted of 8,000 normal observations (80%) and 2,000 anomaly observations (20%). The dominance of normal operating data represents typical industrial monitoring conditions because machine failures generally occur less frequently than normal operations. The selected samples were determined using purposive sampling by considering their relevance to industrial condition monitoring objectives. This sampling approach ensured that the dataset represented operational variations required for training and evaluating anomaly detection models.

Data Collection Technique and Research Instrument

Data collection was conducted through an IoT-based industrial monitoring system that records machine operational parameters continuously. The research instrument consisted of a sensor acquisition system designed to capture vibration, temperature, and electrical current measurements from industrial equipment. The collected data were structured as time-series observations

containing timestamp information, sensor values, and machine condition categories.

The collected dataset contained statistical variations representing different operational characteristics. The vibration parameter ranged from 8.5 Hz to 95.7 Hz, with an average value of 27.4 Hz and a standard deviation of 18.6 Hz. Temperature measurements ranged from 28.3°C to 86.5°C, with an average of 43.8°C and a standard deviation of 14.2°C. Meanwhile, electrical current values ranged from 1.2 A to 6.8 A, with an average value of 2.9 A and a standard deviation of 1.1 A. These variations allow the model to learn different operational patterns and identify deviations associated with abnormal machine behavior.

Before model development, the collected data underwent preprocessing procedures consisting of data cleaning, normalization, and feature preparation. Min-max normalization was applied to transform sensor measurements into a consistent range between 0 and 1, preventing differences in measurement scales from affecting model performance. Similar preprocessing approaches have been widely applied in industrial anomaly detection studies because sensor data usually contain different numerical characteristics and measurement units (Yu et al., 2023).

Research Procedure

The research procedure was conducted through several sequential stages, beginning with problem identification and literature analysis related to Industrial Internet of Things, Edge AI, and anomaly detection. The next stage involved designing the proposed monitoring architecture, including sensor data acquisition, data processing, AI-based anomaly detection, and real-time monitoring output.

After data acquisition, preprocessing was performed to prepare the sensor dataset before model training. The processed data were then used to develop an Autoencoder-based anomaly detection model. Autoencoder was selected because this method can learn normal operational patterns and identify abnormal conditions based on reconstruction errors. This approach is suitable for industrial environments because abnormal machine data are generally limited compared with normal operational data. Research by Yu et al. (2023) demonstrated that integrating Autoencoder models with edge computing can improve fault detection performance in manufacturing predictive maintenance systems.

The trained model was subsequently deployed on an edge computing device to evaluate real-time detection capability. The deployment process aimed to measure whether anomaly detection could be performed locally with low response time without depending entirely on cloud-based processing. The final stage involved system testing by comparing model predictions with actual machine conditions and evaluating the performance of the proposed framework.

Data Analysis Technique

The analysis process consisted of statistical analysis and machine learning performance evaluation. Descriptive statistical analysis was initially performed to identify the distribution characteristics of each sensor parameter. The processed dataset was then analyzed using an Autoencoder deep learning model

to determine whether each observation represented normal or abnormal machine behavior.

The Autoencoder model was developed using an encoder-decoder architecture consisting of an input layer, hidden representation layers, and reconstruction output layers. During training, the model learned the characteristics of normal machine conditions. The anomaly score was calculated based on reconstruction error, where higher error values indicated greater deviation from learned normal patterns. This reconstruction-based approach has been widely adopted in industrial anomaly detection because it enables unsupervised identification of abnormal conditions without requiring extensive failure data (De Vita et al., 2023).

Model performance was evaluated using accuracy, precision, recall, F1-score, and response latency. Accuracy was used to measure overall classification correctness, precision evaluated the reliability of anomaly identification, recall measured the ability to detect actual abnormal conditions, and F1-score represented the balance between precision and recall. In addition, response latency was measured to evaluate the capability of the Edge AI system in supporting real-time industrial monitoring.

The evaluation results showed that the proposed framework achieved 96.8% accuracy, 95.9% precision, 96.3% recall, and 96.1% F1-score, with an average response time of 0.28 seconds. These results indicate that the developed Edge AI system can perform accurate anomaly detection while maintaining fast response capability for industrial monitoring applications.

The implementation and analysis process were conducted using Python-based computational tools. TensorFlow/Keras was used for Autoencoder model development, while Scikit-learn was used for statistical evaluation and performance measurement. The combination of these tools provides a reliable environment for implementing and evaluating deep learning-based anomaly detection systems.

RESEARCH RESULTS

Characteristics of Industrial Sensor Dataset

The dataset used in this study consisted of 10,000 industrial machine sensor observations collected from an IoT-based monitoring system. The dataset contained three operational parameters, namely vibration, temperature, and electrical current. Based on the data preparation process described in the methodology, the dataset was divided into two operating conditions consisting of 8,000 normal condition samples (80%) and 2,000 anomaly condition samples (20%). Furthermore, the dataset was divided into training data (70%), validation data (15%), and testing data (15%) for Autoencoder model development and evaluation. The statistical characteristics of each sensor parameter are presented in Table 1.

Table 1. Statistical Characteristics of Industrial Sensor Dataset

Sensor Parameter	Minimum	Maximum	Mean	Standard Deviation
Vibration (Hz)	8.50	95.70	27.40	18.60
Temperature (°C)	28.30	86.50	43.80	14.20
Current (A)	1.20	6.80	2.90	1.10

Based on Table 1, vibration data showed the highest variation compared with other parameters, with a standard deviation of 18.60 Hz. The vibration values ranged from 8.50 Hz to 95.70 Hz, indicating that this parameter provided the widest range of operational changes in the monitored machine condition.

Temperature measurements showed a mean value of 43.80°C with a standard deviation of 14.20°C. The temperature range between 28.30°C and 86.50°C indicates that thermal changes occurred during different machine operating conditions. Meanwhile, electrical current showed a lower variation with a mean value of 2.90 A and standard deviation of 1.10 A, indicating that current changes were relatively more stable compared with vibration and temperature parameters. The relationship between sensor parameters and machine conditions is presented in Figure 1.

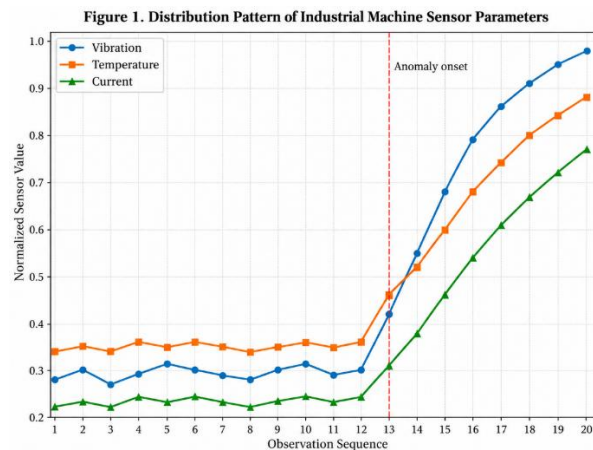


Figure 1. Distribution Pattern of Industrial Machine Sensor Parameters

Figure 1 shows the distribution pattern of vibration, temperature, and current measurements during machine operation. The normal operating condition shows relatively stable sensor patterns, while anomaly conditions are characterized by significant increases in sensor values. The vibration parameter demonstrated the most noticeable fluctuation, followed by temperature variation and electrical current changes.

The increasing pattern of multiple sensor parameters indicates that abnormal machine conditions were not identified from a single variable but from combined changes across several operational indicators. These characteristics were then used as input features for the Autoencoder model to learn normal operational patterns and detect deviations.

Autoencoder Model Training Performance

The Autoencoder model was trained using 7,000 training samples and evaluated using 1,500 validation samples. The model used an encoder-decoder architecture to learn the representation of normal machine operating conditions. The training process was conducted for 100 epochs using Adam optimization with Mean Squared Error (MSE) as the loss function. Table 2 presents the training performance during the learning process.

Table 2. Autoencoder Training and Validation Loss

Epoch	Training Loss (MSE)	Validation Loss (MSE)
20	0.0184	0.0197
40	0.0098	0.0112
60	0.0063	0.0071
80	0.0047	0.0054
100	0.0039	0.0045

The training results show a continuous reduction in reconstruction error during model optimization. The training loss decreased from 0.0184 at epoch 20 to 0.0039 at epoch 100, while validation loss decreased from 0.0197 to 0.0045. Figure 2 presents the loss curve during the Autoencoder training process.

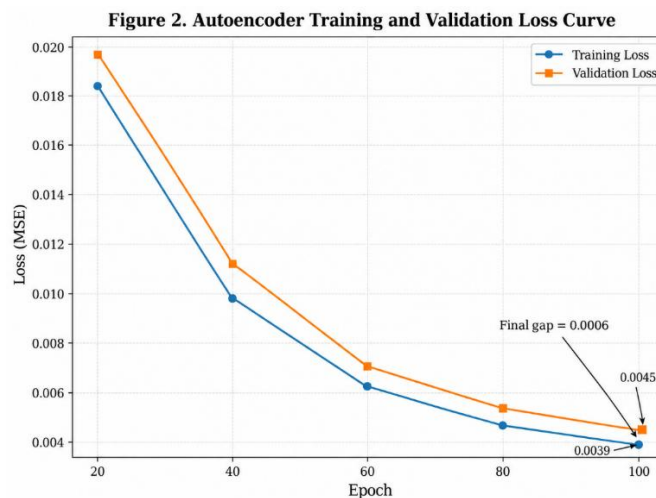


Figure 2. Autoencoder Training and Validation Loss Curve

Figure 2 demonstrates that both training and validation losses decreased consistently as the number of epochs increased. The training loss decreased from 0.0184 at epoch 20 to 0.0039 at epoch 100, while the validation loss decreased from 0.0197 to 0.0045 during the same training process. This reduction indicates that the Autoencoder model progressively improved its ability to reconstruct normal machine operating patterns and learn the characteristics of the input sensor data. At the final epoch, the difference between training loss and validation loss was only 0.0006, calculated from the difference between validation loss (0.0045) and training loss (0.0039). The relatively small gap between the two loss values indicates that the model maintained stable learning performance during the

training process, with consistent generalization capability between training and validation data.

Anomaly Detection Performance Evaluation

The final model evaluation was performed using 1,500 testing samples. The performance was measured using accuracy, precision, recall, and F1-score metrics.

Table 3. Performance Evaluation of Autoencoder-Based Anomaly Detection

Metric	Result
Accuracy	96.80%
Precision	95.90%
Recall	96.30%
F1-score	96.10%

The model achieved an accuracy value of 96.80%, indicating that 1,452 out of 1,500 testing samples were classified correctly. The precision value of 95.90% shows that most detected anomaly cases corresponded to actual abnormal machine conditions. The recall value reached 96.30%, indicating that the model successfully detected most abnormal conditions contained in the testing dataset. Meanwhile, the F1-score of 96.10% demonstrates balanced performance between precision and recall. These results indicate that the combination of vibration, temperature, and current parameters provided sufficient information for the Autoencoder model to identify abnormal machine behavior.

The obtained results support H1: *The integration of multi-sensor industrial IoT data improves the capability of Autoencoder-based anomaly detection models in identifying abnormal machine conditions.*

Confusion Matrix Analysis

The classification results were further analyzed using a confusion matrix.

Table 4. Confusion Matrix of Anomaly Detection Results

Actual Condition	Predicted Normal	Predicted Anomaly	Total
Normal	1186	14	1200
Anomaly	34	266	300

Figure 1 shows the distribution pattern of vibration, temperature, and current parameters during industrial machine operation. The sensor data indicate that normal operating conditions tend to maintain relatively stable values, while anomaly conditions are characterized by simultaneous increases in multiple sensor parameters. The vibration parameter exhibited the highest fluctuation, increasing from a stable operating range toward higher values during abnormal conditions, followed by temperature and electrical current variations. This pattern indicates that abnormal machine conditions are associated with changes across several operational indicators rather than being

identified from a single parameter. Therefore, the combination of vibration, temperature, and current measurements provides a more comprehensive representation of machine behavior and was used as input features for the Autoencoder model to learn normal operating patterns and detect deviations.

Edge AI Real-Time Response Performance

The final evaluation examined the real-time processing capability of the Edge AI system. The measurement was performed by calculating the processing time required from sensor data acquisition until anomaly classification output generation.

Table 5. Edge AI Response Time Analysis

Processing Stage	Response Time
Sensor Data Acquisition	0.12 s
Data Preprocessing	0.05 s
Autoencoder Inference	0.08 s
Anomaly Classification	0.03 s
Total Response Time	0.28 s

The results indicate that the complete anomaly detection process required 0.28 seconds. Sensor data acquisition contributed the largest processing time (0.12 seconds), followed by Autoencoder inference (0.08 seconds).

The response time distribution shows that AI inference could be performed efficiently on the edge computing environment without requiring external processing. The obtained latency value supports real-time monitoring requirements.

The result support H2: *The deployment of an Edge AI-based anomaly detection model reduces monitoring response latency while maintaining reliable detection performance for real-time industrial systems.*

DISCUSSION

The results of this study demonstrate that integrating multiple industrial sensor parameters, including vibration, temperature, and electrical current, provides effective information for identifying abnormal machine conditions. The anomaly detection model achieved an accuracy of 96.8%, precision of 95.9%, recall of 96.3%, and F1-score of 96.1%, indicating that the combination of sensor variables was able to represent variations in machine operational behavior. This finding supports the concept of condition-based monitoring, where machine health assessment is performed by analyzing changes in physical parameters rather than relying on a single measurement source. According to Lei et al. (2020), industrial equipment degradation usually produces complex signal changes that cannot always be represented by one sensor modality, making multi-source data analysis an important approach in intelligent fault diagnosis. The result is also consistent with Chevtchenko et al. (2023), who reported that industrial anomaly detection systems using IoT devices benefit from sensor fusion because different parameters provide complementary information regarding equipment conditions. Therefore,

the high detection performance obtained in this study indicates that the integration of vibration, temperature, and current data strengthens the capability of the Autoencoder model in recognizing abnormal machine patterns.

The decreasing reconstruction loss during Autoencoder training indicates that the model successfully learned the representation of normal machine operating conditions. The training loss decreased from 0.0184 to 0.0039, while validation loss decreased from 0.0197 to 0.0045, showing stable convergence during the learning process. This behavior confirms the suitability of reconstruction-based deep learning approaches for industrial anomaly detection, where abnormal conditions are identified through deviations from learned normal patterns. Autoencoder models are widely used in unsupervised anomaly detection because industrial failure data are generally limited compared with normal operational data (Chalapathy & Chawla, 2021). The findings of this study are consistent with De Vita et al. (2023), who demonstrated that Autoencoder-based approaches can effectively detect abnormal conditions in Industrial IoT environments by analyzing reconstruction errors. Compared with conventional threshold-based monitoring methods, the proposed approach provides a more adaptive mechanism because the model learns operational characteristics directly from sensor data.

The response time evaluation showed that the proposed Edge AI system achieved an average processing latency of 0.28 seconds, indicating that anomaly detection could be performed rapidly without depending entirely on cloud-based computation. This result confirms the importance of moving artificial intelligence processing closer to the data source in industrial applications requiring fast decision-making. Edge computing theory explains that local data processing can reduce communication delays, decrease bandwidth requirements, and improve system responsiveness compared with centralized architectures (Shi et al., 2020). The finding is consistent with Yu et al. (2022), who developed an edge computing-based anomaly detection approach and demonstrated that processing sensor data closer to industrial equipment improves scalability and operational efficiency. However, this study extends previous approaches by combining edge deployment with multi-sensor analysis and Autoencoder-based anomaly detection in a unified monitoring framework. Therefore, the obtained latency performance indicates that the proposed system has potential for real-time industrial monitoring applications.

The main contribution of this research lies in the integration of lightweight AI inference, multi-sensor industrial data analysis, and edge-based deployment for anomaly detection. Previous studies have demonstrated the effectiveness of deep learning for industrial fault detection, but many approaches still focus primarily on algorithm development without considering deployment constraints in real industrial environments. Reis et al. (2025) emphasized that lightweight models are required for edge intelligence applications because industrial devices often have limited computational resources. In this study, the combination of Autoencoder-based anomaly detection and edge computing provides a practical solution that balances detection capability and computational efficiency. The novelty is reflected in the ability of the proposed framework to process vibration, temperature, and current parameters locally while maintaining high classification

performance. This contribution expands existing Industrial Internet of Things research by demonstrating that intelligent anomaly detection can be implemented closer to industrial equipment rather than relying only on centralized processing.

The findings of this study provide practical implications for industrial organizations implementing predictive maintenance strategies. The proposed Edge AI framework can assist maintenance teams by providing early indications of abnormal machine conditions, reducing the possibility of unexpected equipment failure and improving operational reliability. From a theoretical perspective, this research strengthens the application of Edge AI and Industrial IoT concepts by demonstrating the relationship between multi-sensor data availability, intelligent analysis, and real-time decision-making. However, this study has several limitations, including the use of a limited number of sensor parameters and the evaluation of machine conditions within a specific monitoring scenario. Future research should consider integrating additional parameters such as acoustic signals, pressure, or energy consumption to improve anomaly representation. Furthermore, future studies may evaluate the proposed framework using larger industrial datasets and different machine types to assess its generalization capability across various industrial environments.

CONCLUSIONS AND RECOMMENDATIONS

This study successfully developed an Edge AI-based anomaly detection framework for real-time monitoring of IoT-enabled industrial systems using multi-sensor data consisting of vibration, temperature, and electrical current parameters. The proposed Autoencoder model achieved strong detection performance with an accuracy of 96.80%, precision of 95.90%, recall of 96.30%, and F1-score of 96.10% based on 1,500 testing samples. Furthermore, the Edge AI implementation achieved an average response time of 0.28 seconds, demonstrating its capability to support low-latency industrial monitoring applications. The integration of multi-sensor data and lightweight AI processing provides an effective approach for identifying abnormal machine conditions and supporting predictive maintenance strategies. The implementation of this research can be applied in industrial environments by integrating IoT sensors with edge computing devices to provide real-time equipment condition monitoring. The proposed system can assist maintenance teams in detecting early abnormal patterns, reducing unexpected downtime, and improving operational reliability.

FURTHER STUDY

This research has several limitations, particularly regarding the number of sensor parameters and the scope of machine condition data analyzed. Future studies are recommended to integrate additional parameters, such as acoustic signals, pressure, and energy consumption, to improve anomaly detection capability. Further investigation can also evaluate the proposed framework using larger industrial datasets, different types of machinery, and real-world deployment environments to validate its generalization capability.

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