Journal of Computer Science, Information Technology and Telecommunication Engineering (JCoSITTE)
Vol. 6, No. 2, September 2025, pp. 891~900
ISSN: 2721-3838, DOI: 10.30596/jcositte.v6i2.25625

Anomaly Detection on CBTC Wayside Units with the Random Forest Algorithm for Condition-Based Maintenance

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ABSTRACT

This study proposed an anomaly detection model for wayside units in Communication-Based Train Control (CBTC) systems using the Random Forest algorithm. The primary goal was to identify deviations in technical parameters such as voltage, temperature, humidity, and signal strength (RSL) that may indicate potential failures in the system. Data were collected from IoT-based sensors deployed on MRT Jakarta's CBTC wayside units and transmitted via HTTP to a cloud database for further processing. The Random Forest model was trained using labeled data and evaluated using unseen test data. The evaluation metrics, accuracy, precision, recall, and F1-score, reached 100%, indicating that the model correctly identified both normal and anomalous conditions without misclassification. Further analysis showed that high humidity, excessive panel temperature, and low RSL values were the most frequent anomaly indicators. Based on this, the system also generated maintenance recommendations, making it not only reactive but also proactive in supporting condition-based maintenance (CBM). The results demonstrated that the Random Forest-based anomaly detection system is highly effective, scalable, and reliable for real-time monitoring of railway infrastructures. This approach can serve as a foundation for future development of smart maintenance systems in other safety-critical domains.

Keyword : Anomaly Detection; Random Forest; Condition-Based Maintenance; CBTC; IoT Monitoring.

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Article history:
Received Jul 4, 2025
Revised Jul 20, 2025
Accepted Aug 26, 2025

1. INTRODUCTION

Urban railways are pivotal to metropolitan mobility and economic activity; consequently, their reliability must be kept high. Between 2022 and 2023, Jakarta's MRT carried 53.18 million passengers (BPS DKI Jakarta, 2024). Indonesia's Ministry of Transportation regulates the maintenance of track, stations, and operational facilities, while certified personnel are mandated to ensure safety (Jonge & Scarf, 2019; Kementerian Perhubungan Republik Indonesia, 2017b, 2017a, 2018; Peraturan Menteri Perhubungan Republik Indonesia Nomor 22 Tahun 2021 Perizinan Penyelenggaraan Prasarana Perkeretaapian Umum, 2021). Given this passenger load, conventional preventive and corrective maintenance alone is no longer sufficient.

Railway signalling applies fixed-block and moving-block principles (Anders et al., 2020; Gupta, 2022; Kementerian Perhubungan Republik Indonesia, 2017c). Communication-Based Train Control (CBTC), a moving-block system, relies on two-way 2.4 GHz communication between on-board and wayside units to manage speed and headway (Fakhereldine et al., 2023; Gao et al., 2022; IEEE, 2004; Song et al., 2020). The wayside unit's reliability underpins operational safety, yet its performance is highly sensitive to environmental temperature, humidity, and supply-voltage fluctuations.

Excessive temperature (>40 °C), humidity (>80 %), or unstable voltage accelerate component ageing and degrade signal quality (Agbolade & Sunmola, 2021; Alvan Prastoyo Utomo et al., 2019; Medina-Santiago et al., 2020). Consequently, Condition-Based Maintenance (CBM), which continuously monitors actual equipment conditions, offers a proactive solution (Koons-Stapf, 2015; Li et al., 2020; Olde Keizer et al., 2018; Prabhakar P & v. P., 2019; Teixeira et al., 2020; Wiboonrat, 2019). Machine-learning-enhanced CBM has already predicted failures in marine engines, photovoltaics, and hydro power, proving its early-warning capability (Berghout et al., 2021; Coraddu et al., 2014; Karlsson et al., 2020; Paolanti et al., 2018; Qi et al., 2020).

Nevertheless, the literature in Table 1 shows that railway CBM research still centres on rolling stock, interlocking, and point machines, often using vibration or current data and unsupervised methods; environmental variables and automatic CBM advice for CBTC wayside units remain unaddressed (Allah Bukhsh et al., 2019; Guzman et al., 2020; Sousa Tomé et al., 2023; YOKOUCHI et al., 2022; Zuo et al., 2023). This constitutes the primary research gap tackled in this study.

Table 1. Summary of Prior Studies

No	Author	Object / Data	Algorithm /Focus	Key Result	Research Gap
1	Bukhsh *et al.*	1.7 million switch-and-crossing logs – Netherlands	Decision Tree, Random Forest, Gradient-Boosted Trees → predict "need", activity type & trigger status	Accuracy > 90 %; model interpretable via LIME	Does not address CBTC wayside units or environmental variables
2	Zuo *et al.*	Switch/crossing vibration & acoustics (Sweden)	Isolation Forest anomaly score + Laplacian feature ranking	Rail-squat detection; automatic thresholding	Unsupervised; no CBM recommendations; mechanical focus—no voltage/temperature/RSL
3	Sousa Tomé *et al.*	Metro do Porto interlocking logs (7 months)	Two-phase pipeline: anomaly detection → online RUL prediction	Early point-machine anomaly detection; streaming prototype	No IoT-sensor integration; voltage and signal quality not assessed
4	Guzman *et al.*	Point-machine motor current & power (DLR)	Unsupervised statistical-feature extraction + forecasting	Reduced false-alarm rate	Focus on actuator motor; excludes RSL/communication; not Random Forest
5	Yokouchi *et al.*	Diesel-engine coolant-temperature & train-AC blowing-temperature logs (monthly)	LSTM-based anomaly detection; anomaly score from estimation error	Predicted engine over-heat 1.5 h before emergency stop; detected AC degradation 1.5 months before crew report	Not CBTC wayside; no voltage/RSL monitoring; deep-learning focus, lacks CBM recommendation module

To bridge the gap, this work installs an IoT sensor network on MRT Jakarta's CBTC wayside units, to collecting samples of voltage, temperature, humidity, and Receive Signal Level (RSL). The dataset is processed within a supervised-learning framework using a Random Forest algorithm to detect anomalies, rank feature importance, and generate condition-based maintenance recommendations, a departure from prior CBTC research that centred on network-level simulations or system-level sensor-fusion design (Hasma & Silfianti, 2018; Nazaruddin et al., 2019).

This framework is elaborated in Section 2 Research Method, detailing the sensor architecture, data-acquisition procedures, preprocessing techniques, anomaly-labelling strategy, Random Forest hyper-parameter tuning, and evaluation protocol. The methodological exposition is intended to facilitate replication across other urban-rail networks and to ensure full traceability of every technical decision taken in the study. Hence, the narrative flows seamlessly from the background to the research methods while underscoring the scientific contribution sought.

2. RESEARCH METHOD

This section outlines the methodological framework employed in this study, detailing each step from system design to model evaluation. The research adopts a quantitative, engineering-based approach to detect anomalies in wayside units of Communication-Based Train Control (CBTC) systems using supervised machine learning. Each methodological phase, sensor integration, data acquisition, pre-processing, model training, and evaluation, is designed to ensure scientific reproducibility and operational relevance. By combining real-time IoT sensing with a Random Forest classifier, the method enables early fault detection and supports condition-based maintenance (CBM) strategies.

A. Research Procedure

This study is generally divided into three stages: the Design Stage, the Implementation Stage, and the Analysis Stage, as illustrated in Figure 1.

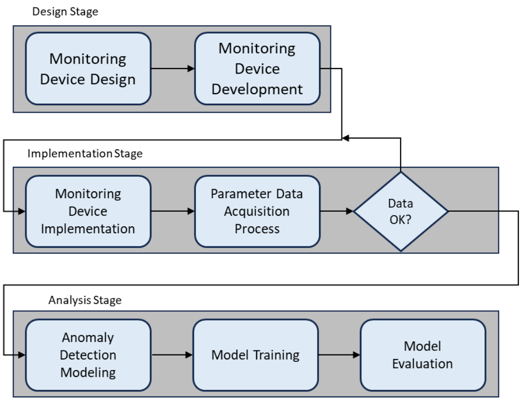


Figure 1. Research Procedure

The research began by designing and constructing an IoT-based monitoring device to observe critical parameters on CBTC wayside units, such as voltage, temperature, humidity, and RSL. This phase involved selecting appropriate sensors, determining installation locations, and designing a communication system to automatically and periodically transmit data to a server. Once the device was fully assembled, it was installed at designated CBTC wayside units. The system was configured to operate autonomously, ensuring continuous and valid sensor data acquisition for further analysis.

The Random Forest algorithm was employed using a supervised learning approach to develop the anomaly detection model. This process involved selecting relevant predictor features and tuning model parameters such as the number of decision trees (*n_estimators*) and maximum tree depth (*max_depth*). The data were labeled as normal or anomalous based on predefined technical thresholds. The trained model was then tested using a separate test set that had not been used during training. Model performance was evaluated using accuracy, precision, recall, and F1-score metrics to measure the model's classification ability in distinguishing between normal and anomalous data in real-world field conditions.

B. Research Design

This study employs a quantitative method with an experimental approach. Primary data were collected from a CBTC wayside unit located on the elevated track of Jakarta MRT, covering parameters such as voltage, temperature, humidity, and RSL. An ESP32-based IoT sensor system automatically transmitted the data via Wi-Fi using the HTTP protocol to a cloud database. The collected data were then used as a dataset to train an anomaly detection model using the Random Forest algorithm. The block diagram of the modeling stage is presented in Figure 2.

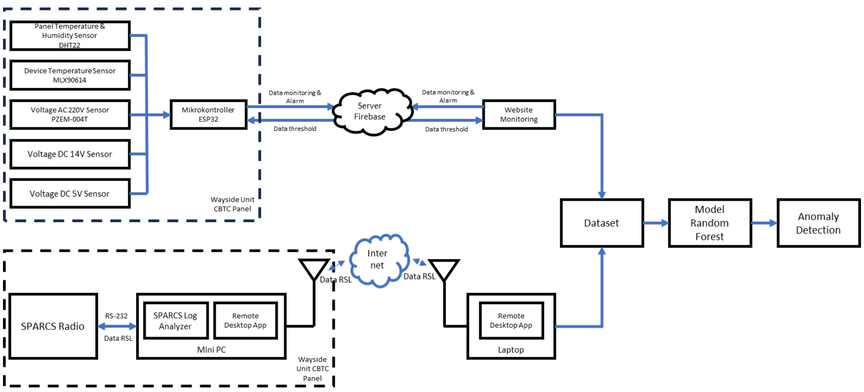


Figure 2. Block Diagram of the Modeling Stage

C. Data Acquisition

The research data were collected using an ESP32-based IoT sensor with a 60-second sampling interval. The monitored parameters include input and output power supply voltage, device temperature, panel air temperature and humidity, and Receive Signal Level (RSL). These values were measured based on predefined technical thresholds which mentioned in Table 2. Collected data were automatically transmitted to a cloud database via HTTP protocol and stored in a database table along with a timestamp.

Table 2. Technical thresholds for monitored parameters of CBTC wayside unit

No	Parameter	Unit	Normal Technical Threshold
1	Input Power Supply Voltage (Vin)	VAC	220 VAC ±10%
2	Output Power Supply Voltage (Vout)	VDC	14 VDC ±5% and 5 VDC ±5%
3	Device Temperature (TMP DEV)	°C	≤ 40°C
4	Panel Air Temperature (TMP PANEL & HMD PANEL)	°C	≤ 40°C
5	Panel Air Humidity	%RH	≤ 80%
6	RSL	dBm	≥ -70 dBm

D. Design and Development of an Anomaly Detection Model Using Random Forest

This section outlines the anomaly detection model designed using the Random Forest algorithm. The model is implemented in Python using the scikit-learn library, supported by pandas, NumPy, and matplotlib/seaborn for data processing and visualization. The model architecture consists of three main components: the Input Layer (containing six sensor features including voltage, temperature, humidity, and RSL), the Random Forest Layer (involving bootstrap sampling, random feature selection, and an ensemble of decision trees), and the Output Layer which delivers final predictions via majority voting. The full architecture is illustrated in Figure 3.

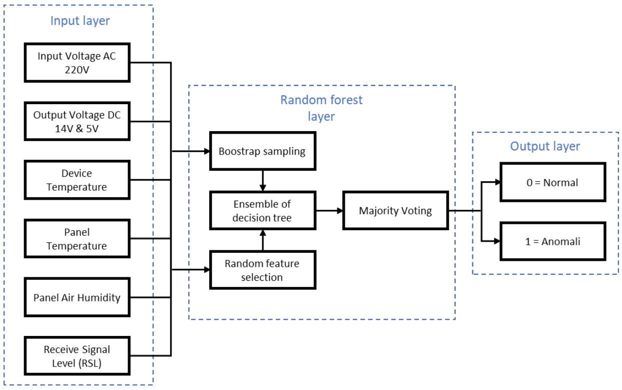


Figure 3. Anomaly Detection Architecture Using Random Forest

Model evaluation is conducted using metrics such as accuracy, precision, recall, and F1-score, as well as probability scores to reflect classification confidence. Random Forest is selected for its high accuracy, robustness to imbalanced data, and stable outputs. Another key advantage is its ability to compute feature importance, which enhances the interpretability of which variables most influence anomaly detection (Dinova & Prasetiyo, n.d.). The model has also shown strong performance across domains, including medical diagnostics and cyberattack detection (Dinova & Prasetiyo, n.d.; Harto & Basuki, 2021).

E. Anomaly Detection Model Testing

This section outlines the evaluation stages for the anomaly detection model based on the Random Forest algorithm. Testing was performed using unseen test data to evaluate the model's generalization performance. The steps, illustrated in Figure 4.

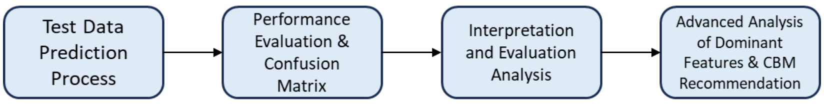


Figure 4. Anomaly Detection Model Testing Stages

1. The first step is test data prediction, where the trained Random Forest model is used to classify each row in the test set as either 'normal' (label 0) or 'anomaly' (label 1). The classification is

based on a *majority voting* mechanism across all decision trees in the model. The prediction results are then stored for further analysis.

2. The second stage involves performance evaluation through a confusion matrix that compares model predictions with the actual labels (ground truth). From the matrix, the following evaluation metrics are computed:

$$\boxed{Accuracy = \frac{True\ Positive + True\ Negative}{True\ Positive + True\ Negative + False\ Positive + False\ Negative}} \quad (1)$$

$$\boxed{Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}} \quad (2)$$

$$\boxed{Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}} \quad (3)$$

$$\boxed{F1 - Score = 2\ x\ \frac{Precision\ x\ Recall}{Precision + Recall}} \quad (4)$$

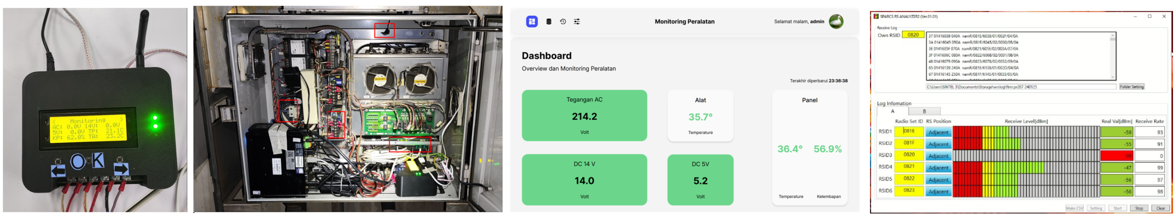
These metrics provide a comprehensive picture of the model's ability to detect anomalies accurately.

3. The third step is evaluation interpretation, which starts with reviewing the confusion matrix to determine whether False Positives or False Negatives are dominant. This is followed by assessing the balance between precision and recall, and comparing the metrics with predefined thresholds to assess implementation readiness. Additionally, error trends are reviewed to guide revisions in features, sampling, or model parameters in the next iteration.
4. The final step is advanced analysis of dominant features contributing to anomalies. This begins with utilizing the Random Forest's *feature importance* scores to quantify each variable's contribution. Then, the distribution of critical values in anomaly data is mapped, followed by counting the frequency of each feature's appearance in anomalous rows. These insights are translated into CBM recommendations, such as prioritizing inspections of high-temperature panels or verifying voltage supply if Vout frequently appears alongside anomalies.

3. RESULTS AND DISCUSSION

3.1. Monitoring System Implementation

To support data collection for the development of an anomaly detection system on CBTC wayside units, an IoT-based monitoring system was designed and implemented. This system monitors key parameters including input/output voltage, device temperature, panel temperature and humidity, as well as RSL. Monitoring results are transmitted to a server and displayed in a real-time web dashboard. The implementation results are shown in Figure 5.



(a) (b) (c) (d)

Figure 5. IoT-based monitoring system results,
(a) ESP32 and sensor based monitoring tool, (b) Installation of monitoring tool on CBTC wayside unit panel, (c) Monitoring website, (d) RSL monitoring value.

3.2. Data Acquisition Result

The monitoring system collected key parameters including Vin 220V, Vout 14V & 5V, TMP DEV, TMP PANEL, HMD PANEL, and RSL A/B that mentioned five sample record in Table 3. Initial sample records confirmed stable voltage conditions, while notable variations were observed in temperature and humidity within the panel.

Table 3. Five sample record raw data

Timestamp	Vin_220V	Vout_5V	Vout_14V	TMP DEV	TMP PANEL	HMD PANEL	RSL A	RSL B
2025-01-24 00:59:59	214V	5.1582V	13.9943V	26.6086°C	26.4152°C	90.2135%	-59	-44
2025-01-24 01:01:51	214V	5.1659V	13.9859V	26.6025°C	26.4728°C	89.6610%	-60	-47
2025-01-24 01:02:58	214.0379V	5.1679V	13.9958V	26.5615°C	26.4169°C	89.6627%	-58	-47
2025-01-24 01:04:07	214.0828V	5.1615V	14.0013V	26.5859°C	26.3999°C	89.7457%	-58	-44
2025-01-24 01:05:12	214.0897V	5.1646V	13.9973V	26.7174°C	26.4423°C	89.7694%	-55	-44

3.3. Anomaly Detection Model Testing Result

Model testing was conducted to evaluate the performance of the anomaly detection system using a test set that had not been seen during training. Each record in the test data was classified into two categories: normal (label 0) or anomaly (label 1) using a Random Forest model that applies a majority voting mechanism. The classification is based on key input features such as voltage, temperature, humidity, and RSL.

As shown in Table 4, all five sample records from the test data were classified as anomalies (label 1), which matched the manually labeled ground truth. This alignment indicates that the model effectively recognized patterns reflecting anomalous conditions, at least in this data subset.

Table 4. Model prediction results

Record	Test Data (key features)	Actual Label	Model Prediction
1	214.0; 13.9; 5.1; **90.2**; 26.4; 26.6; -59; -44;	1	1
2	214.0; 13.9; 5.1; **89.6**; 26.4; 26.6; **-60**; -47;	1	1
3	214.0; 13.9; 5.1; **89.6**; 26.4; 26.5; -58; -47;	1	1
4	214.0; 14.0; 5.1; **89.7**; 26.3; 26.5; -58; -44;	1	1
5	214.0; 13.9; 5.1; **89.7**; 26.4; 26.7; -55; -44;	1	1

Further analysis was conducted to identify which technical features most frequently appeared in records classified as anomalies. As shown in Figure 6, the top three features with the highest anomaly frequencies are:

- Panel temperature exceeding the operational safety limit of 40°C,
- RSL B signal falling below the threshold of -60 dBm,
- Panel humidity reaching or exceeding 80%.

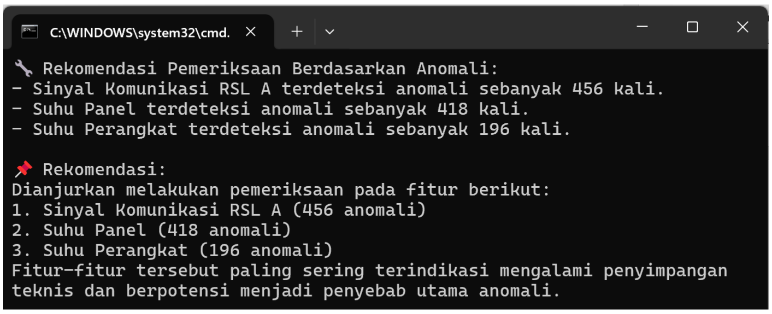


Figure 6. Examination recommendation results

These features consistently appeared in anomalous data and are considered critical indicators of equipment malfunction. Therefore, as part of the Condition-Based Maintenance (CBM) approach, the system can proactively suggest physical or technical inspections for relevant device components, such as panel cooling systems, RSL antenna modules, or airflow and humidity control systems inside the panel. This integration transforms the anomaly detection system from a passive monitor into a proactive decision-support tool, aligning with one of CBM's core principles: early fault prevention through intelligent diagnosis.

Model performance was evaluated by comparing prediction results to actual labels (ground truth) using a confusion matrix, as outlined in Table 4.10. The structure of this matrix is described in Table 4.9, consisting of four key components: True Positive (TP), False Positive (FP), True Negative (TN), and False Negative (FN). From a total of 3,638 records (3,121 normal and 517 anomalies), the confusion matrix was:

Table 5. Confusion matrix

	Predicted Normal	**Predicted Anomaly**
Actual Normal	3121 (TN)	0 (FP)
Actual Anomaly	0 (FN)	517 P)

The evaluation metrics calculated from this matrix are:
- Accuracy = (3121 + 517) / 3638 = 100%
- Precision = 517 / (517 + 0) = 100%
- Recall (Sensitivity) = 517 / (517 + 0) = 100%
- F1-Score = 2 × (1.0 × 1.0) / (1.0 + 1.0) = 100%

These results demonstrate that the anomaly detection model using Random Forest achieved highly optimal performance, with zero misclassifications. No false positives or false negatives were observed, confirming the model's ability to accurately detect both normal and anomalous conditions. The perfect precision implies no false alarms, which is crucial for maintaining user trust in automated monitoring systems. The recall score of 100% ensures that all anomalies were successfully detected, which is vital for safety in CBTC (Communications-Based Train Control) systems. The flawless F1-score reflects a well-balanced capability to detect anomalies accurately while avoiding misclassification, making the model highly suitable for real-world applications such as CBTC system monitoring.

3.4. Discussion

The Random Forest-based anomaly detection model demonstrated outstanding performance across all evaluation metrics, achieving 100% accuracy, precision, recall, and F1-score. These results suggest an excellent ability to distinguish between normal and anomalous conditions in CBTC wayside units. The confusion matrix confirmed zero false positives and zero false negatives, indicating the model's robustness in real-world classification tasks. This level of performance, although ideal, may be influenced by a high degree of data separation and the suitability of the selected features, namely voltage, temperature, humidity, and RSL.

These results align with previous studies that reported high performance of Random Forest in infrastructure monitoring tasks (Allah Bukhsh et al., 2019; Guzman et al., 2020), yet this study offers novel contributions by integrating environmental parameters such as temperature, humidity, and RSL, factors not previously emphasized in CBTC anomaly detection. Furthermore, the study leverages feature importance analysis to pinpoint the most critical variables causing anomalies, providing explainable insights for maintenance personnel.

From a Condition-Based Maintenance (CBM) perspective, this research successfully transitions anomaly detection from a diagnostic tool to a decision-support system. The system not only identifies fault conditions but also generates maintenance recommendations based on the frequency and severity of anomalies detected in specific features. For instance, frequent humidity-related anomalies may prompt checks on the panel's ventilation or sealing, while voltage deviations suggest inspection of the power supply system. This proactive approach could significantly enhance maintenance effectiveness and reduce system downtime.

Despite these promising outcomes, further testing under more diverse operational conditions is necessary to validate the model's generalizability. Future work could also explore integration with real-time alerts, edge computing deployment, and comparative analysis with deep learning models to assess performance scalability. Nonetheless, this study provides a replicable and technically sound framework for anomaly detection in CBTC systems using interpretable and high-performing machine learning models.

4. CONCLUSION

This research successfully demonstrates the implementation of an anomaly detection model on CBTC wayside units using the Random Forest algorithm. As expected from the objectives stated in the Introduction, the system was able to identify normal and anomalous conditions based on technical features such as voltage, temperature, humidity, and RSL signal strength. The model achieved perfect performance in evaluation metrics 100% accuracy, precision, recall, and F1-score, confirming its ability to classify real-world data with no misclassification.

The results align with the hypothesis that Random Forest can serve as a reliable machine learning model for condition-based maintenance (CBM) systems. Furthermore, the system not only detects anomalies but also provides recommendations based on the most frequent and significant technical deviations, supporting proactive maintenance decision-making.

In terms of future development, this study opens opportunities for real-time deployment and integration with edge computing systems, particularly in critical infrastructure monitoring. Further studies are recommended to validate model generalization under diverse environmental and operational conditions, as well as compare its performance with deep learning-based methods. The findings of this research provide a solid foundation for scalable, explainable, and high-performance anomaly detection solutions in transportation infrastructure.

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