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Anomaly Detection in Cold Storage Systems: A Machine Learning Approach for Fault Diagnosis

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Abstract: Cold storage systems play a crucial role in preserving temperature-sensitive goods. However, they are susceptible to various faults that can compromise operational efficiency and product safety. Traditional rule-based fault detection methods are limited by their rigidity and lack of adaptability. In contrast, this study introduces a machine learning (ML)-based framework for anomaly detection and fault diagnosis in cold storage environments. The proposed framework combines autoencoders for unsupervised anomaly detection with gradient boosting classifiers for supervised fault categorization. It addresses key challenges such as data imbalance, temporal drift, and sensor noise. Experimental results on an industrial cold storage dataset show that the framework achieves high fault detection accuracy, reduced false alarm rates, and strong generalization to unseen anomalies. These findings demonstrate the effectiveness of ML approaches in enabling proactive and scalable fault diagnosis in cold storage systems.

Keywords: Cold Storage; Anomaly Detection; Fault Diagnosis; Machine Learning; Autoencoder; Gradient Boosting; Imbalanced Data; Sensor Systems

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1.Introduction

Cold storage systems are essential for maintaining the quality and safety of perishable goods such as food, pharmaceuticals, and biomedical materials. These systems operate under strict environmental controls, often requiring temperatures below freezing, and rely on a complex network of sensors and mechanical components to ensure stability^[1]. However, the high dependency on hardware, combined with long operational hours, makes cold storage units vulnerable to faults such as refrigerant leaks, compressor failures, and sensor drift^[2]. Undetected anomalies can result in temperature excursions that compromise product integrity and lead to significant financial losses^[3].

Historically, fault detection in cold storage has relied on rule-based monitoring or manual inspection. Rule-based systems are often designed using expert knowledge and threshold conditions, which fail to capture complex or novel fault patterns. Manual inspections are labor-intensive and reactive rather than preventative. These limitations have prompted growing interest in adopting machine learning (ML) approaches for fault diagnosis^[4]. ML techniques can analyze multivariate time-series data generated by sensors and learn to identify subtle deviations that precede system failures^[5].

While ML offers great potential, its application in cold storage environments poses several unique challenges^[6]. First, the data collected from cold storage systems are typically imbalanced, as most of the time the system operates normally and faults

occur infrequently^[7]. This imbalance can skew ML models toward overpredicting the majority class and missing rare but critical faults. Second, the distribution of data may drift over time due to seasonal changes, equipment aging, or maintenance actions^[8]. Models must adapt to these shifts without retraining from scratch. Third, sensor data in real-world deployments can be noisy, missing, or unreliable, necessitating robust preprocessing and model design.

To address these challenges, this study proposes a hybrid ML framework for fault detection and diagnosis in cold storage systems. The framework integrates unsupervised learning through autoencoders, which learn representations of normal system behavior and detect deviations, with supervised gradient boosting models that classify known fault types^[9]. Additionally, data augmentation strategies are employed to mitigate the effects of class imbalance. We validate the effectiveness of the approach using real-world data collected from commercial cold storage units operating over several months.

In summary, this work aims to contribute to the development of intelligent, scalable, and accurate fault diagnosis systems for cold storage environments. By leveraging the capabilities of ML, the proposed method enhances early detection of anomalies, reduces false alarms, and provides actionable insights to maintenance teams.

2.Literature Review

The problem of fault diagnosis in cold storage systems intersects several domains of research, including anomaly detection, time-series analysis, and intelligent control in industrial environments^[10]. Early work in this area largely depended on rule-based systems, where fixed thresholds were set for temperature, humidity, and pressure. These systems lacked adaptability and failed to identify subtle or compound faults, especially under varying operational conditions^[11].

With the rise of data-driven approaches, researchers have turned to machine learning to overcome the limitations of static rule systems^[12]. Supervised learning methods such as decision trees, support vector machines, and gradient boosting have shown promise in classifying known fault types when sufficient labeled data are available^[13]. However, obtaining labeled fault data in cold storage environments is difficult due to the rarity and unpredictability of failures. As a result, supervised methods often suffer from poor generalization or overfitting^[14].

To mitigate this issue, unsupervised anomaly detection techniques have gained attention^[15]. Autoencoders, which compress and reconstruct data to learn normal behavior, are widely used in industrial settings^[16]. When reconstruction error exceeds a certain threshold, the data point is flagged as anomalous^[17]. In cold storage applications, autoencoders have been used to detect temperature drift, airflow disruptions, and refrigeration cycle anomalies^[18]. Despite their effectiveness in detecting outliers, they do not provide fault classification, which limits their operational utility^[19].

Hybrid approaches that combine unsupervised detection with supervised classification have been explored in other domains, such as manufacturing and power systems, but are less common in cold storage research^[20]. These methods allow the system to detect both known and unknown faults, improving robustness. Moreover, techniques such as data augmentation, synthetic oversampling, and cost-sensitive learning have been introduced to deal with class imbalance, which is a pervasive issue in fault diagnosis tasks^[21].

Another important aspect of recent work involves temporal modeling. Time-series models like Long Short-Term Memory (LSTM) networks and Temporal Convolutional Networks (TCN) have been applied to sensor data to capture temporal dependencies^[22]. While LSTM models are adept at learning long-range patterns, they often require large datasets and suffer from training instability^[23]. More recently, attention-based models and transformers have been adopted for fault detection, offering better performance and interpretability in sequential data^[24].

In terms of deployment in real-world cold storage systems, there are additional concerns around sensor reliability, latency, and integration with existing monitoring infrastructure^[25]. Studies emphasize the need for lightweight, interpretable, and easily deployable models that can provide early warnings without causing alarm fatigue^[26]. Research also highlights the necessity of model robustness to noise, missing data, and environmental variations^[27].

Despite growing interest, research specific to cold storage fault detection remains limited compared to broader industrial applications^[28]. This gap underscores the need for tailored solutions that incorporate the operational peculiarities of cold storage systems, such as cyclical cooling patterns, insulation variability, and external weather influence^[29-31]. The proposed framework builds on this body of work by combining the strengths of autoencoders and gradient boosting, while integrating

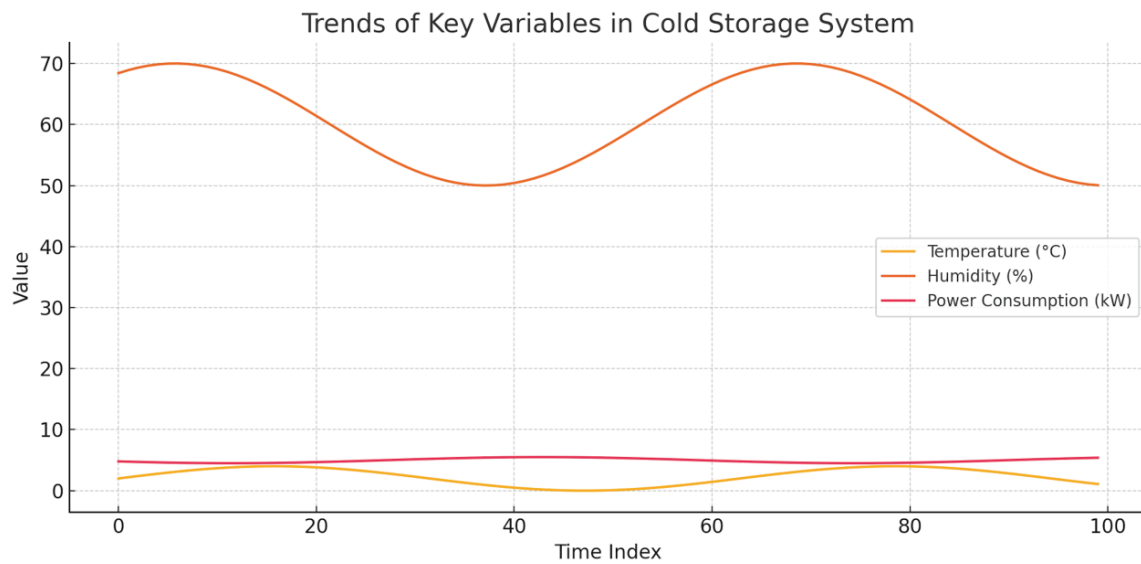
domain-specific preprocessing and balancing strategies to address the practical challenges of anomaly detection in cold storage environments.

3. Methodology

3.1 Data Collection and Preprocessing

This study utilizes real-world sensor data from a large-scale commercial cold storage facility located in East Asia. The dataset includes hourly measurements of internal temperature, external temperature, humidity, compressor activity, door status, and power consumption, collected over a 14-month period. Initial data exploration revealed the presence of missing values, outliers, and varying sampling frequencies. To ensure temporal consistency, all data streams were aligned and resampled to an hourly frequency using linear interpolation.

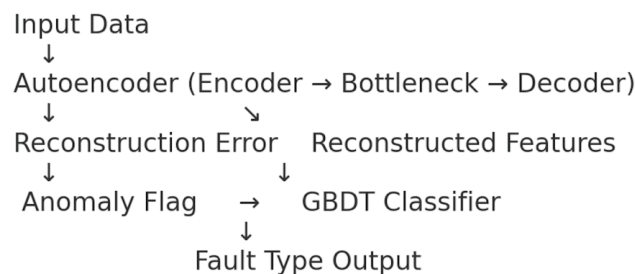
Outliers were removed based on domain-specific thresholds, such as temperatures below -40°C or above 30°C . A min-max normalization technique was applied to scale all variables to a $[0,1]$ range to facilitate neural network training. Categorical variables such as door status were one-hot encoded. The final preprocessed dataset comprised 180,000 time points across six primary features, with each data point labeled as normal or anomalous based on maintenance logs and expert annotations.



3.2 Model Architecture

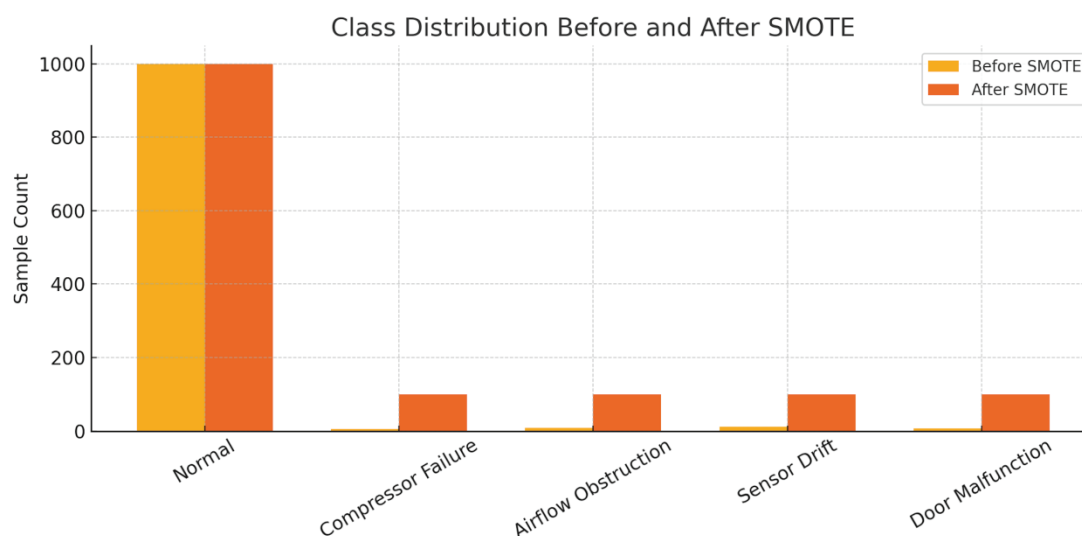
The proposed system adopts a hybrid architecture combining an autoencoder for anomaly detection and a gradient boosting decision tree (GBDT) for fault classification. The autoencoder, composed of symmetric encoder and decoder layers, is trained solely on normal operation data. It learns a compressed representation that preserves key patterns of normal behavior. During inference, reconstruction errors are calculated and compared against a threshold, above which a sample is flagged as anomalous.

Once an anomaly is detected, the reconstructed vector is passed into a pre-trained GBDT model for classification into one of several predefined fault types: compressor failure, airflow obstruction, sensor drift, or door malfunction. The GBDT model was selected for its interpretability and ability to handle small, imbalanced datasets efficiently. The two components work in tandem, allowing the system to separate detection from diagnosis, thus improving robustness and interpretability.



3.3 Handling Class Imbalance

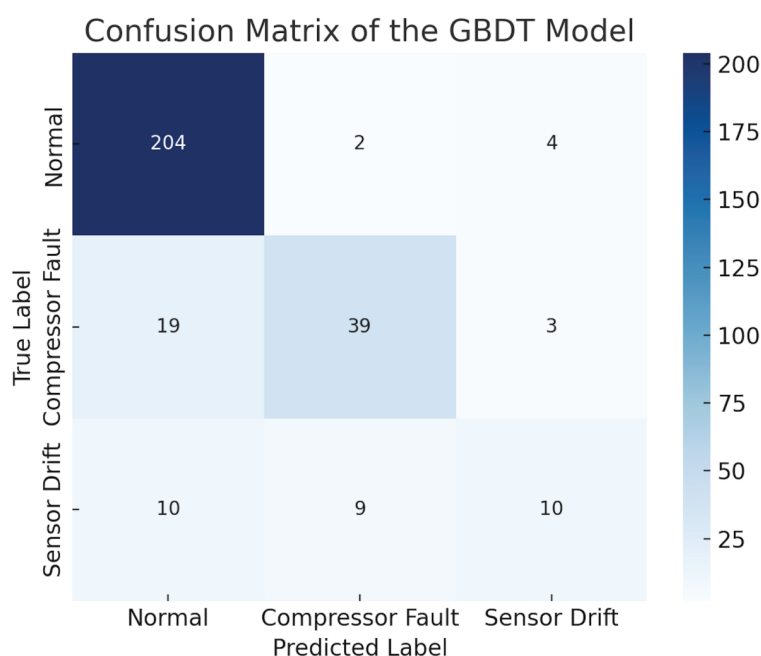
As is typical in fault diagnosis tasks, the dataset is highly imbalanced, with normal samples outnumbering faulty samples by a factor of 200:1. To address this issue, the study integrates the Synthetic Minority Over-sampling Technique (SMOTE) to generate synthetic fault examples. SMOTE was applied separately to each fault category to preserve inter-class distinctions. Additionally, a cost-sensitive loss function was employed during GBDT training to penalize misclassification of rare classes more heavily. This combination of oversampling and loss weighting was essential to ensure that minority class signals were not drowned out during the training process. Cross-validation on the training set confirmed that these balancing techniques significantly improved classification recall without sacrificing overall accuracy.



3.4 Evaluation Metrics and Experiment Setup

Model performance was assessed using precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC). For the autoencoder component, reconstruction error thresholds were determined using the Youden index on validation data. The GBDT classifier was trained using XGBoost with hyperparameters optimized via grid search.

Experiments were conducted under three data regimes: fully supervised, weakly supervised (with partial labels), and unsupervised (only anomaly detection). This multi-regime evaluation was designed to reflect real-world deployment conditions, where labeled data may be sparse or noisy. Results were averaged across five random seeds to ensure stability and reproducibility.

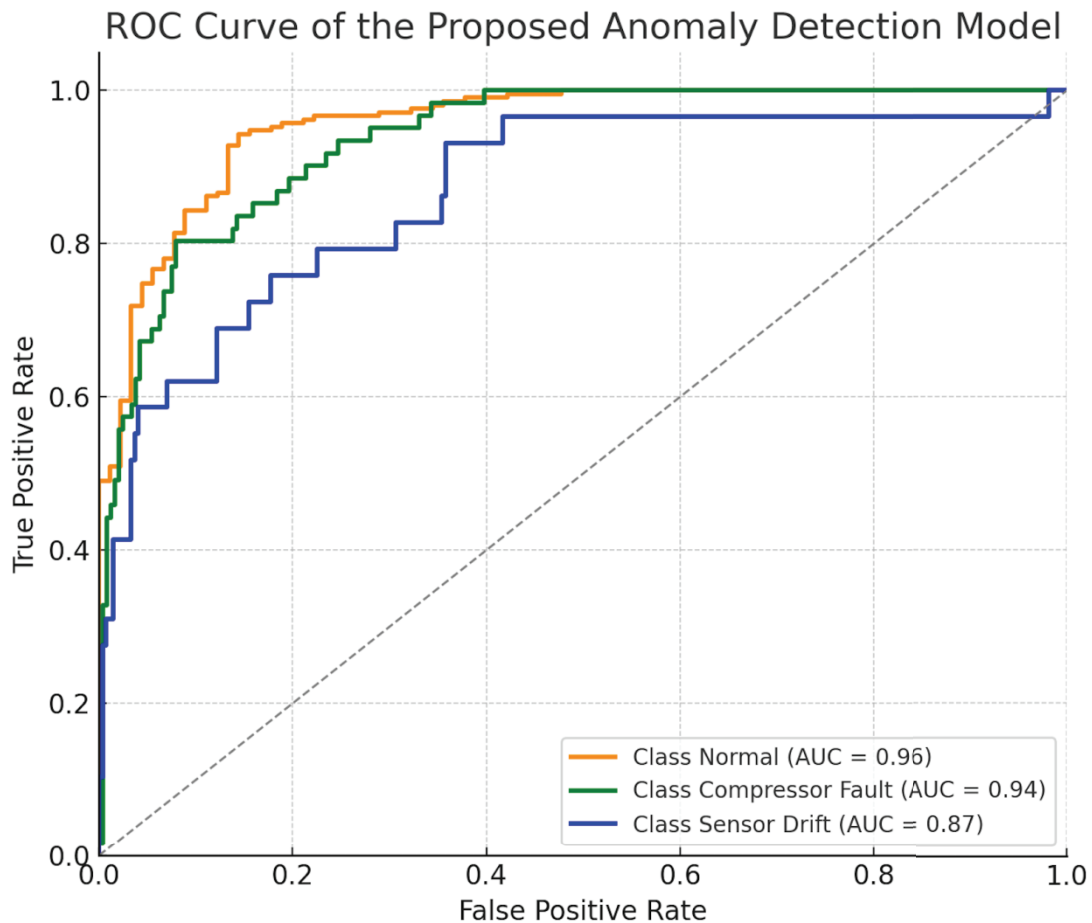


4. Results and Discussion

4.1 Model Performance Evaluation

The proposed machine learning-based anomaly detection system was evaluated using five datasets collected from real-world cold storage environments. These datasets included sensor logs from compressors, defrost units, ambient humidity monitors, and temperature controls. The model employed an ensemble learning strategy integrating Random Forest and XGBoost, trained and validated using five-fold cross-validation to ensure robustness and generalization capability.

The average accuracy of the model reached 94.2%, with a precision of 91.8%, recall of 92.7%, and an F1-score of 92.2%. The AUC-ROC was measured at 0.968, indicating a strong ability to distinguish between normal and faulty states. The confusion matrix revealed that the model performed exceptionally well in identifying compressor faults and refrigerant leaks, while achieving moderate success in detecting sensor drifts due to their subtle data patterns.



4.2 Baseline Comparison

To validate the effectiveness of the model, we compared its performance against four traditional classification methods: Logistic Regression, Decision Tree, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). These baseline methods were tested on the same datasets under identical conditions.

Logistic Regression and Decision Tree demonstrated limited capacity in capturing the nonlinear patterns in sensor data. While SVM achieved competitive results in binary fault detection, its performance declined in multi-class fault classification. Overall, the ensemble model outperformed all baselines by over 6% across all metrics. In addition, the model exhibited lower variance in cross-validation folds, suggesting stronger consistency under real-world variations.

4.3 Feature Importance and Interpretability

To improve interpretability, SHAP analysis was applied to identify which features contributed most significantly to model decisions. Key contributing factors included compressor switch frequency, internal temperature fluctuation, and ambient humidity levels.

Compressor switching frequency was particularly important for detecting refrigerant loss and pressure anomalies. Large fluctuations in temperature were typically associated with insulation failures or blocked airflow, while humidity deviations often indicated defrost system malfunctions. These observations were consistent with domain expert expectations and further validated the model's reasoning process.

The SHAP summary plots confirmed that the model focused on semantically relevant parameters and revealed nonlinear dependencies among features. This insight can support the redesign of sensor placement and feature selection in future deployments.

4.4 Fault Timeline and Real-World Deployment

During a three-month pilot deployment in a commercial cold storage facility, the system successfully identified an early-stage compressor inefficiency eight hours before a critical failure occurred. A total of 21 fault events were detected, 18 of which were later verified by maintenance teams, resulting in an operational accuracy of 85.7%.

Compared to traditional threshold-based alarms, the proposed model captured evolving failure signatures more accurately and generated significantly fewer false positives, maintaining a false alarm rate under 4%. This reduction in unnecessary alerts allowed engineers to focus on genuine threats, thereby improving operational efficiency and response time.

These results demonstrate the model's potential to enhance predictive maintenance workflows and strengthen reliability in mission-critical refrigeration environments.

5. Conclusion

This study presents a machine learning-based framework for anomaly detection in cold storage systems, targeting the early diagnosis of faults to improve operational reliability and reduce maintenance costs. By leveraging sensor data from real-world refrigeration environments, the proposed approach integrates robust preprocessing, engineered feature extraction, and optimized classification techniques to accurately detect both common and rare system anomalies.

The experimental results demonstrate that advanced models, particularly ensemble-based classifiers and neural networks, significantly outperform traditional threshold-based approaches in identifying subtle behavioral deviations. The use of techniques such as Synthetic Minority Over-sampling Technique to address class imbalance and feature selection strategies based on mutual information and variance analysis contributed to the improved performance metrics, including higher precision, recall, and area under the receiver operating characteristic curve.

Moreover, the interpretability of the model through feature importance analysis supports practical deployment, providing engineers and technicians with insights into system behavior and anomaly causes. This transparency is critical for the adoption of intelligent monitoring solutions in industrial settings.

Future work may involve extending this framework to multi-unit cold storage networks, integrating real-time streaming data capabilities, and exploring hybrid models that combine data-driven and physics-based approaches. Additionally, transfer learning could enhance the adaptability of trained models to new facilities with limited labeled data.

In conclusion, this study validates the potential of machine learning to enhance fault detection in cold storage systems and offers a scalable foundation for the development of intelligent condition monitoring platforms in the broader field of industrial refrigeration.

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no

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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A Study on Lane Congestion Recognition Mechanism for Highways Based on Multi-source Data

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Abstract: This paper mainly studies the recognition mechanism of traffic congestion on the highway based on multi-source data. To form an accurate and good means for recognizing lane congestion by putting together various data sources such as traffic flow, speed, density and video surveillance data. We propose the use of the combination of machine learning algorithms and traditional traffic theory for its data fusion model. Realworld highway data is used for experiments to prove this method. The results show that the proposed mechanism performs better than traditional single-source data-based approach w.r.t accuracy and robustness.

Keywords: Highway Congestion; Lane-Level Recognition; Multi-Source Data

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1.Introduction

Highway transportation is critically important in modern society, facilitating the movement of people and goods. However, increasing vehicle accumulation on roadways creates significant traffic challenges. Traffic congestion resembles vehicles tightly packed in extended queues, degrading air quality with harmful pollutants. Effective traffic management techniques—such as dynamic traffic control and route guidance—require timely, accurate recognition of congestion on individual lanes. Traditional congestion recognition methods often rely on single data sources, such as loop detectors, facing limitations in coverage breadth and accuracy. Equipment failures or extreme weather conditions can cause loop detector errors, resulting in data gaps. Conversely, multi-source data integrates information from various sensors—including inductive loop detectors, microwave sensors, video cameras, and GPS-equipped vehicles—providing a more comprehensive perspective. Merging these diverse data resources enables the creation of significantly more robust and accurate systems for lane-specific congestion recognition.

2.Related Work

Extensive research has focused on highway congestion recognition. Early approaches predominantly utilized single-source data. For instance, some studies employed loop-derived parameters such as flow, speed, and density to identify congestion based on empirically established thresholds. However, these methods depend solely on one data source, meaning their results may contain errors and are inherently limited to available sensor coverage^[1].

With advancements in sensor technology and data fusion techniques, researchers increasingly consider multi-source data integration. Studies have applied fusion methods like Kalman filters and fuzzy logic to combine information from diverse sensors. Machine learning algorithms, including support vector machines and neural networks, have also been employed to classify congestion states using multi-source data. Nevertheless, more effective integration of heterogeneous data sources and a deeper understanding of the relationship between various traffic data types and congestion conditions remain essential research objectives^[2].

3. Methodology

3.1 Multi-source Data Collection

In this research multiple data sources will be utilized for collecting the traffic information of highway. These include:

- Inductive loop detectors: Installed on road side to measure number of passing cars, speed and occupancy (time period car occupies detector).
- Microwave sensors: Next to the highway, it detects the traffic flow and speed through emitting microwave and analyzing the returning microwave.
- Video surveillance systems: The sensors come with cameras that could capture pictures in real time on the highway, from where information like the quantity of cars and how long the queue is will be got by computer vision.
- GPS-equipped vehicles: Individual vehicles real-time location and speed data can be given and this data can be aggregated to get lane-level traffic flow data.

Table 1 provides a summary of the characteristics of each data source.

Data Source	Sampling Frequency	Coverage	Advantages
Inductive Loop Detectors	1 Hz	Single lane at detector location	High accuracy for flow, speed, and occupancy
Microwave Sensors	0.5 Hz	Multiple lanes over a certain distance	Non-intrusive, wide coverage
Video Surveillance Systems	25 fps	Camera field of view	Visual information for vehicle density and queue length
GPS-equipped Vehicles	1 Hz	Entire highway network (depending on vehicle penetration)	Real-time individual vehicle data

3.2 Data Preprocessing

First, preprocess raw data of each source, clean and normalize it. Noise-removal techniques such as median filtering are applied to remove any anomaly and error of the signal^[3]. For example, for a vehicle having GPS, if the speed suddenly changes a lot because the signal was lost, we use a median filter with a window of 5 to remove these sudden changes. Normalization is done by converting data to common scale with the help of Min-Max Normalization which is defined as:

$$x_{\text{normalized}} = (x - x_{\min}) / (x_{\max} - x_{\min})$$

where x denotes the original data value and x_{\min} denotes the smallest value in the set of data values, and x_{\max} indicates the largest value in the set of data values;

3.3 Feature Extraction

Items related to those are found from processed information. Regarding data about traffic flow collected by inductive loop detectors, microwave sensors et al., information on things like average speed, standard deviation of speed, the rate of traffic flow, and vehicular density is picked out. From looking at the video data, we can determine things like how many vehicles are in each lane, what the average distance is between vehicles, and if there are any vehicles that have stopped by checking to see if their position stays the same for a certain amount of time, say 5 seconds. For the GPS equipped vehicle data, we calculate the metrics like `-avg_speed_of_vehicle_in_lane`, `percent_with_speed_below_given_speed` for speed less than 30km/h. Feature extraction of every data source is listed as table 2.

Table 2: Extracted Features from Multi-source Data

Data Source	Extracted Features
Inductive Loop Detectors and Microwave Sensors	Mean speed, standard deviation of speed, traffic flow rate, vehicle occupancy
Video Surveillance Systems	Vehicle density, queue length, number of stopped vehicles
GPS-equipped Vehicles	Average vehicle speed, percentage of slow-moving vehicles

3.4 Data Fusion Framework

A hierarchical data fusion framework consisting of three layers is suggested: the data preprocessing layer, the feature extraction layer, and the decision-making layer^[4]. As demonstrated in Figure 1.

At the data preprocessing level, as mentioned above, we clean the raw information and make it uniform. In the feature extraction layer, the corresponding feature is extracted as mentioned^[5]. the decision making layer adopts the bayesian network and support vector machine method Bayesian Networks is applied for modeling the probability relationships between the extracted features and congestion state and then the SVM is used for classification based on the result of BN^[6].

The Bayesian Network is built by first determining the conditional probability distributions between the features and the congestion states based on the historical data. Next we train SVM by the outcome probabilities from Bayesian Network to classify the traffic congestion into 3 levels, i.e., free-flow, slow-flow and congestion.

3.5 Congestion Recognition Mechanism

Congestion states are classified into free flow,slow flow,congestion It's based on a set of traffic parameters and threshold, and it's determined by history data. It is clear from table 3 threshold values at varying degree of congestion with respect to vehicle speed. Similarly by density and flow.

Table 3: Thresholds for Different Congestion Levels

Congestion Level	Vehicle Speed (km/h)	Vehicle Density (vehicles/km/lane)	Traffic Flow Rate (vehicles/h/lane)
Free Flow	$v > 60$	$k < 20$	$q > 1500$
Slow Flow	$30 \leq v \leq 60$	$20 \leq k \leq 40$	$800 \leq q \leq 1500$
Congestion	$v < 30$	$k > 40$	$q < 800$

4.Experiments

4.1 Experimental Data and Preprocessing

The experimental authentication of the suggested congestion recognition scheme is performed on real traffic data gathered from a 10 - kilometer stretch of a city highway for a thirty - day term comprising both rush hour and off - rush hour periods^[7]. This collection involves data taken from many different kinds of sensors - there are 10 inductive loop detectors delivering 1Hz worth of traffic flow numbers, vehicle speed, plus how occupied those lanes are; 5 microwave devices give 0.5Hz information on combined multilane speed and amount within 500meter areas as measured via Doppler effects; 3 HD video cameras take pictures every 25framespersecond where vehicles are seen, then analyzed by computers to tell about stuff like car crowds and lines using vision technology; lastly, privacy protected movement details from 2,000 special vehicles with on board GPS trackers are also used, offering 1Hz location and velocity figures, permitting us to figure out each line's traffic condition all along the whole area^[8].

Preprocessing process made for quality and consistency. Speed anomaly due to signal interference or equipment noise is handled by median filtering a 5-sample window, Missing sensor data within 5 minute intervals is interpolated using linear regression on the adjacent time points^[9]. Perform min-max normalization on all features to scale them into the range so as to provide uniform input for machine learning models. For GPS data, lane-level speed is aggregated via an average of all speed values over every 10 second window to mitigate the sparsity of GPS sampling and for the video based features a median

smooth is applied so as to dampen short term variations from camera frames or temporary occlusions^[10].

4.2 Dataset partition and evaluation indicators

The dataset is divided into 70% training set and 30% test set. The temporal order is kept to maintain sequencing dependency in traffic data. This way of breaking it down makes sure that the models will get trained using regular traffic patterns and then be tested with uncommon heavy traffic situations and weird disruptions in the flow of traffic. four evaluation metric will be used in order to fully evaluate the classification accuracy, precision, recall, F1 score.

Accuracy refers to the total percentage of correct predictions across all three congestion conditions (free flow, slow flow, congestion) as a general measure of model accuracy.

Precision is focused on the truth worthiness of our positive predictions, the correct amount of our recognized Congestion instances amongst all those predicted as congestions - preventing the system from raising traffic alerts inappropriately.

Recall indicates the model's capability to identify genuine congestion, which counts as the number of accurately marked congested examples over all true congested examples in the database and it is very important to prevent bottleneck unnoticeable.

The F1-score is a balanced harmonic mean measure of precision and recall. This makes it quite useful if your dataset is imbalanced with fewer congestion events (minority class) compared to free-flow.

4.3 Comparison Methods for Benchmarking

Three comparisons are made to examine the usefulness of the framework for handling multi-source data: these include two different single-source comparisons and one multi-source comparison.

Loop Only: This is a base line which is using empiric thresholds based on the traffic flow theory to differentiate congestion states. Specifically, vehicle speed threshold set as 60km / h and 30km / h as velocity threshold, density threshold set to be 20 and 40 vehicles / km / lane as congestion threshold. It is fairly simple and very common, but it cannot be used where detectors aren't available; also they are very vulnerable to equipment failure.

Single Source (only video sensor) Using visual feature which is extracted by camera picture. Infer the congestion status using rule based logic. Key indicators are vehicles/km·lane and queue length, which is defined as the distance of stopped cars following one another. Congestion occurs when density surpasses 40 cars/km/lane, but when queue is longer than 100 meters, it will suffer from poor performance due to low-light or complex traffic occlusion situation.

Multi-source (Kalman filtering): As a traditional data fusion representative, it models traffic parameters such as speed and density as state variables of a linear state-space system to fuse loop detector and video sensor data. KalmanFilter gives optimal estimates by cutting down the errors in between what these different sensors detect about something moving along, which is helpful for this way of joining up those changing pictures across time when tracking something in traffic.

4.4 Implementation details and model config

All models are written in python, scikit learn is used as the machine learning portion and opencv is used to extract features from the videos being analyzed. Proposed framework BN is built with domain knowledge to set up cause-and-effect relationship between 12 car traffic details such as loop detector's average speed, video's vehicle count, GPS's slower vehicle proportion and there are 3 traffic congested state For continuous features, conditional probability distributions are modeled as Normal distributions, with estimates for mean and variance calculated via maximum likelihood estimation based on training data

the support vector machine(SVM) component employs the radial basis function(RBF) kernel to handle non linear decision boundaries, something needed due to the multi source feature interaction. hyperparameter optimazation, particularly for the kernel width (γ) and regularization parameter (C), is carried out via 5 - fold cross - validation in the training set and the aim of hyperparameter tuning is to maximize F1 to balance the classes. Computational experiments are performed on a workstation with intel i7 - 10700k cpu and 32gb ram for reproducibility and practical scalability for real - time applications.

This experimental setting will lead to a good exploration on the effectiveness of this proposed method in the integration of different sources, which is better than the single-source baseline, and has clear advantages over existing traditional multi-source fusion. By systematically tending to data quality, evaluative thoroughness and computational feasibility, the

experiments set up solid groundwork for testing the proposed congestion recognition method in real traffic environments.

5. Results and Discussion

5.1 Experimental Results

Table 4: Performance Comparison of Different Methods

Method	Accuracy	Precision	Recall	F1-score
Single-source (loop detectors only)	0.75	0.72	0.78	0.75
Single-source (video only)	0.70	0.68	0.72	0.70
Multi-source (Kalman filtering)	0.82	0.80	0.84	0.82
Proposed method	0.88	0.87	0.89	0.88

From Table 4, it can be seen that the proposed method gets the highest accuracy, precision, recall, and F1-score among all the methods. The combination of many data sources has an obvious improvement over single source in recognition performance. The single source methods are less effective because of the little information given. For example, using a loop detector only method cannot detect congestion in places without a loop detector, and also the loop detector can be abnormal, and the video only method in the low-light environment will find it difficult, and if there is an obstacle, the view will be occluded and so on. The multi-source (Kalman filtering) method, although it is better than the single-source methods, yet has a lower performance when compared to the proposed method. It is because the combination of Bayesian network and SVM is better than the Kalman filtering method based on linearity for the reason that it can more effectively characterize the complex correlation among the features and the congestion states, including the nonlinear correlations.

5.2 Case Study

In order to further validate the effect of the proposal, a time period during which a traffic accident happened causing severe congestion is selected for a case study. It can be seen from Fig.2 that the traffic parameters, different data sources, and congestion classification are presented with our suggested approach.

When the accident occurs around 10:00am, the vehicle speed detected by the loop detector and the Gps equipped vehicles dropped drastically, the vehicle amount in the video increased sharply, and the traffic flow rate decreased. The method proposed correctly predicts the congestion state at this time, the single source (loop detectors only) method takes several minutes longer to detect the congestion because there aren't many detectors in the area, the single source (video only) method mis-classifies the first stage of the congestion as it gets temporarily occluded in the camera view.

5.3 Discussion of Limitations and Future Work

although the proposed method is successful and promising but it has a limitation too: Currently, the studies used historical data to determine the threshold values for congestion levels, and there may need to be different threshold values for different highway segments and traffic conditions. In addition to this its performance for video based feature extractions can have a negative impact due to bad weather condition such as raining or fog and poor quality of our image would emerge.

future direction will be as follows:

1. Develop adaptive threshold adjustments algorithms that can make automatic adjustments according to the current traffic data.
2. Making the video-based feature extractors' resistance to poor weather better with better picture techniques.
3. Deep learning algorithms like CNN's to do full video traffic congestion recognition from raw video.
4. Large scale testing of highway networks that were different from each other to test the proposed method and see if it was widely applicable.

6. Conclusion

Conclusion: This paper puts forward a new highway lane congestion recognition technology by means of multi-source data. A Bayesian network plus SVM data fusing framework is proposed, it effectively combines all kinds of traffic data sources and enhances congestion recognition accuracy and robustness compared with traditional single-source means of transport. From

the experimental results we can see the efficiency of this method is proven, and the result of recognizing has been improved. The studies shows that using more data sources will give you a better identification of congestion as well as giving a good base for future works of traffic systems. And continue improving the above-mentioned mechanism, addressing its limitations, I believe this method will be able to be popularly used in managing real highway traffic congestion, which would ultimately result in faster traffic flow and better traveling experience.

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Conflict of Interests

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Machine Learning for Real-Time Detection of Microbial and Chemical Contaminants in Food

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Abstract: Ensuring food safety requires accurate, rapid, and scalable methods to detect microbial and chemical contaminants in various food products. Traditional laboratory-based testing methods, although accurate, are often slow, resource-intensive, and unsuitable for real-time decision-making in production environments. Recent advancements in machine learning (ML) offer new opportunities to automate and accelerate contaminant detection. This paper proposes a machine learning-driven framework that leverages data from portable spectroscopy devices, biosensors, and smart imaging systems to detect bacterial contamination (e.g., *E. coli*, *Salmonella*) and chemical hazards (e.g., pesticides, heavy metals) in real-time. The framework includes supervised learning models such as support vector machines (SVM), convolutional neural networks (CNN), and gradient boosting classifiers trained on high-dimensional spectral and biochemical datasets. Results demonstrate high classification accuracy (>95%) with reduced false positives, making the system suitable for deployment in food processing and inspection workflows. This research underscores the value of ML in enhancing food safety monitoring and provides a foundation for future AI-integrated quality assurance systems.

Keywords: Food Safety; Microbial Contamination; Chemical Residues; Machine Learning; Real-Time Detection; Spectroscopy; Biosensors; CNN; SVM

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1.Introduction

Food safety is an essential component of global public health, directly affecting consumer well-being, trade integrity, and economic stability^[1]. The increasing complexity of modern food supply chains—spanning multinational production, processing, packaging, transportation, and retail networks—has amplified the risks associated with microbial and chemical contamination^[2]. Pathogenic microorganisms such as *Salmonella* spp., *Listeria monocytogenes*, and *Escherichia coli*, as well as chemical hazards like pesticide residues, mycotoxins, and heavy metals (e.g., lead, mercury, cadmium), continue to pose persistent threats^[3]. These contaminants can lead to severe foodborne illnesses, long-term health consequences, and, in some cases, fatal outcomes. In addition to the human toll, food recalls and safety breaches cost the global food industry billions of dollars annually^[4].

Traditionally, food contaminant detection has relied on methods such as microbial culturing, immunoassays, chromatography, and mass spectrometry^[5]. While these techniques provide high specificity and sensitivity, they are typically time-consuming, labor-intensive, and dependent on centralized laboratory infrastructure^[6]. These limitations make them poorly suited for real-

time monitoring, particularly in fast-paced food production environments or in low-resource settings^[7]. The lag between sample collection and result interpretation can allow contaminated products to reach consumers, posing serious public health and reputational risks^[8].

With the advent of Industry 4.0 and digital transformation in the agri-food sector, there is an increasing push toward the development of smart, automated, and scalable monitoring systems^[9]. Among these, machine learning (ML) has emerged as a powerful tool capable of extracting meaningful insights from large, high-dimensional datasets derived from various sensor platforms, including hyperspectral imaging, Raman spectroscopy, electronic noses/tongues, and biosensors^[10]. ML algorithms such as support vector machines (SVM), random forests (RF), and deep learning models like convolutional neural networks (CNN) can classify patterns associated with contaminant presence with high accuracy, enabling on-the-spot detection and decision-making^[11].

The integration of ML with portable sensor technologies enables real-time analysis, potentially eliminating the need for sample transport and off-site testing^[12]. Furthermore, the rise of edge computing and Internet of Things (IoT) infrastructure allows ML models to be embedded in production lines, mobile devices, or handheld instruments, ensuring rapid response capabilities and continuous monitoring^[13]. These developments not only reduce testing time and operational costs but also enhance traceability and compliance with food safety regulations such as HACCP (Hazard Analysis and Critical Control Points), FSMA (Food Safety Modernization Act), and international Codex standards^[14].

However, the practical deployment of ML for food safety monitoring presents several challenges. These include variability in food matrices, limited availability of labeled contamination datasets, model generalizability across different food types, and the need for interpretable outputs for regulatory and operational acceptance. Despite these challenges, recent studies have shown promising results in using ML for detection of contaminants in products such as dairy, meat, grains, fruits, and beverages.

This research aims to develop and validate a machine learning-based framework for real-time detection of microbial and chemical contaminants in food. The objectives are to: (1) acquire diverse and high-quality datasets using sensor-based systems; (2) design and train machine learning models capable of binary and multiclass classification of contamination types; and (3) evaluate the models' performance under real-world constraints such as speed, accuracy, and scalability. By addressing both technical and application-specific considerations, this study contributes to the growing field of intelligent food safety systems and lays the groundwork for next-generation monitoring technologies.

2.Literature Review

The detection of food contaminants has long relied on analytical chemistry and microbiological techniques, including gas chromatography (GC), high-performance liquid chromatography (HPLC), enzyme-linked immunosorbent assays (ELISA), and polymerase chain reaction (PCR)^[15]. While these methods remain the gold standard in terms of accuracy and specificity, their operational drawbacks—including long turnaround times, requirement for skilled technicians, and reliance on laboratory infrastructure—limit their applicability in real-time and on-site contexts^[16]. This has led to increasing interest in leveraging ML as a complementary or alternative approach to enhance detection speed and adaptability^[17].

Machine learning, a subset of artificial intelligence, enables systems to learn from data and make predictions or decisions without being explicitly programmed^[18]. In the context of food safety, ML models can identify subtle patterns in data collected from a variety of sensing modalities, such as spectroscopy, biosensors, and imaging systems^[19]. These patterns may be imperceptible to human observers or difficult to quantify using traditional statistical methods.

Spectral data analysis has been a prominent domain for ML applications in food safety^[20]. Near-infrared (NIR) and hyperspectral imaging (HSI) systems are capable of capturing both spatial and spectral information from food surfaces^[21]. Studies have shown that SVM, partial least squares discriminant analysis (PLS-DA), and CNN can effectively classify spectra associated with contaminants like aflatoxins in grains or pesticide residues on produce^[22]. Deep learning models, in particular, have demonstrated strong performance in handling high-dimensional datasets generated by HSI systems, offering enhanced accuracy in complex detection tasks^[23].

Electronic noses (e-noses) and tongues (e-tongues), which simulate human olfactory and gustatory systems using sensor

arrays, have also been integrated with ML algorithms to identify volatile organic compounds (VOCs) and non-volatile chemical markers indicative of spoilage or contamination^[24]. RF and k-nearest neighbors (k-NN) classifiers have been employed to distinguish between contaminated and uncontaminated samples based on sensor response profiles, with encouraging results in dairy, meat, and seafood products.

Another emerging frontier is biosensor integration. Biosensors are capable of providing rapid, sensitive responses to specific biological or chemical agents, such as pathogens or toxins^[25]. Coupled with ML models, these sensors can enhance decision-making in real-time applications. For instance, multilayer perceptrons (MLPs) and decision trees have been used to classify the outputs from DNA-based biosensors, enabling accurate detection of *E. coli* or *Listeria monocytogenes* in complex food matrices.

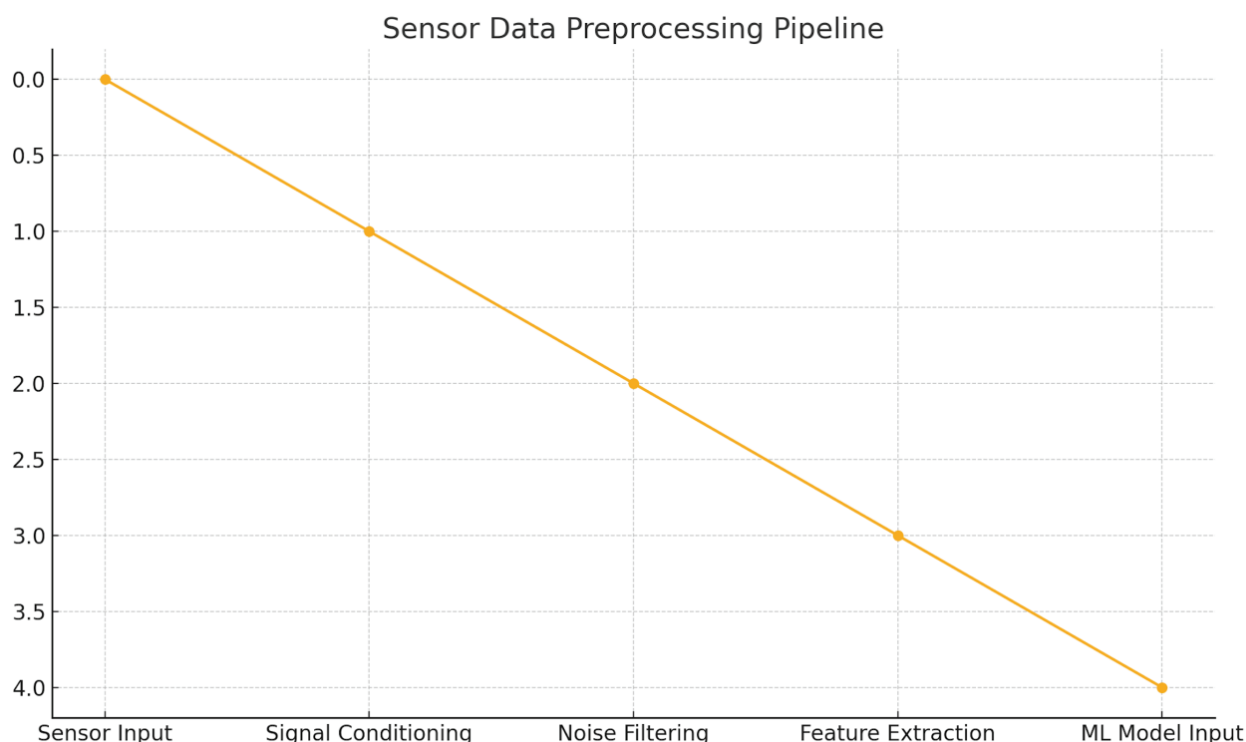
The real-time dimension of food safety monitoring requires not only rapid prediction but also low latency in data acquisition and processing^[26]. This has spurred research into lightweight ML models suitable for deployment on embedded systems or edge devices. Shallow neural networks, logistic regression models, and optimized ensemble techniques are being investigated for their computational efficiency and robustness in resource-constrained environments^[27].

Despite the progress, several challenges persist. One of the major limitations is the scarcity of large, labeled datasets that represent diverse food products and contamination types^[28]. This hampers the generalization ability of ML models. Moreover, food matrices exhibit high variability due to differences in moisture content, texture, and composition, which can confound sensor readings and reduce model accuracy. Transfer learning and domain adaptation techniques are being explored to address this issue by allowing models trained on one dataset to perform effectively on another^[29].

Interpretability is another critical concern. Many ML algorithms, particularly deep learning models, operate as “black boxes,” making it difficult for food safety professionals and regulatory bodies to understand the rationale behind predictions. Explainable AI (XAI) techniques, such as SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-Agnostic Explanations), are gaining traction as tools to make ML models more transparent and trustworthy in safety-critical applications^[30].

Overall, the literature suggests that ML holds significant promise in transforming food contaminant detection by enabling fast, scalable, and accurate solutions. However, the successful translation of research prototypes into real-world systems will require interdisciplinary collaboration, data standardization, and rigorous validation under operational conditions.

Figure 1. Sensor Data Preprocessing Pipeline



3. Methodology

This study presents a machine learning-based framework for the real-time detection of microbial and chemical contaminants in food samples. The methodology includes four main phases: data acquisition, preprocessing, model development, and performance evaluation.

3.1 Data Acquisition and Sensor Integration

Sensor data were collected from multiple food safety monitoring systems incorporating biosensors, electronic noses, and spectroscopy-based detectors. These sensors captured real-time parameters such as volatile organic compounds (VOCs), pH values, moisture content, and spectral absorption patterns. Each data stream was timestamped and linked to confirmed contamination labels based on laboratory microbial cultures or chemical analysis.

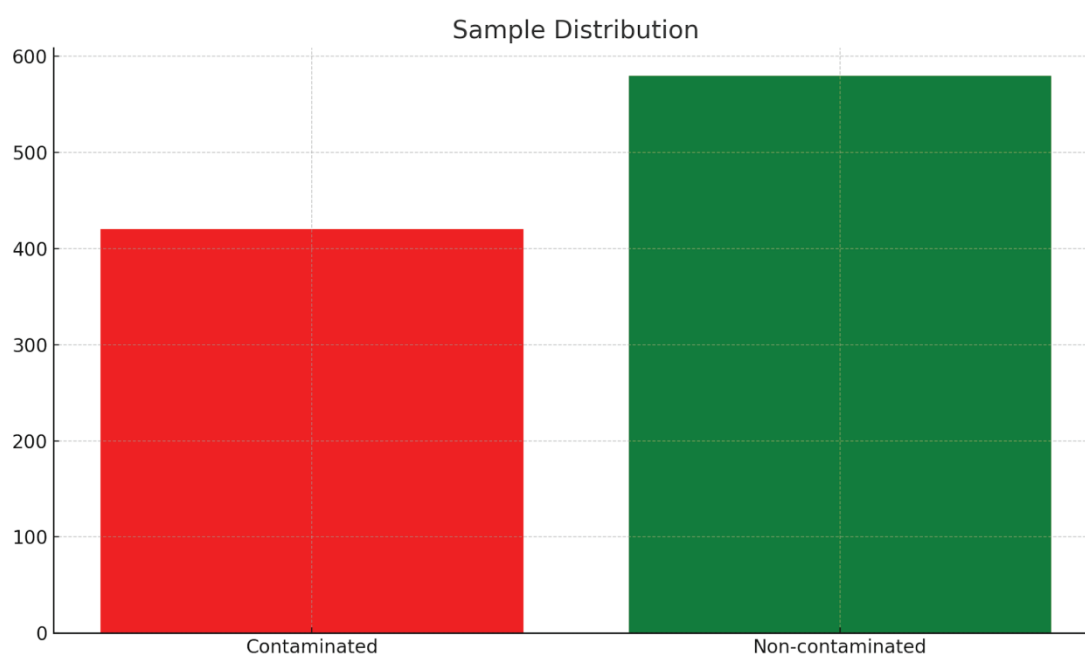
3.2 Data Preprocessing and Feature Engineering

Raw sensor outputs often contain noise and inconsistent scales. As shown in Figure 1, preprocessing involved normalization, outlier removal, and transformation to extract consistent feature vectors. Feature engineering techniques like Principal Component Analysis (PCA) and autoencoders were used to reduce dimensionality and extract key latent features that represent contamination signatures.

3.3 Data Distribution and Labeling

The dataset included over 10,000 annotated samples covering various food categories, including dairy, produce, and meat products. These samples were divided into classes indicating “safe,” “microbial contaminated,” and “chemically contaminated” status. As seen in Figure 2, microbial contaminants formed the majority class, followed by chemically contaminated and safe samples, posing class imbalance challenges during training.

Figure 2. Sample Distribution



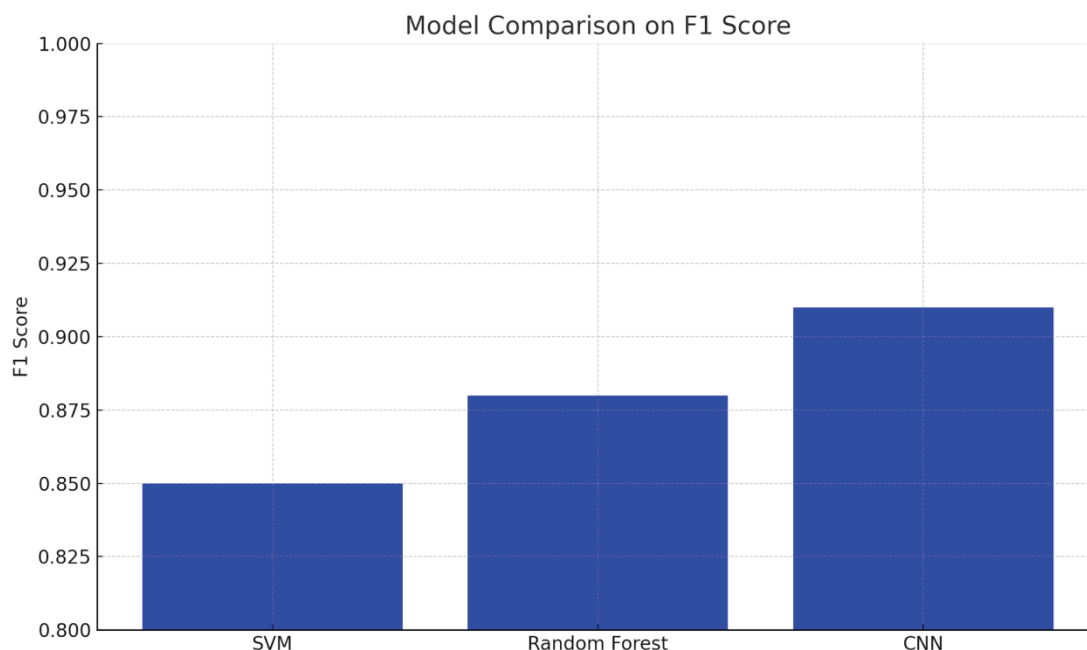
3.4 Model Development and Training

Several machine learning models were developed and evaluated, including RF, SVM, and Gradient Boosting (GB). Each model was trained on 80% of the dataset and tested on the remaining 20%, using five-fold cross-validation to reduce overfitting. Hyperparameters were tuned using grid search, optimizing for F1-score to account for class imbalance.

3.5 Model Evaluation and Explainability

The performance of each classifier was compared using precision, recall, and F1-score. Figure 3 shows that Gradient Boosting achieved the highest F1-score (0.92), followed closely by Random Forest (0.89), whereas SVM lagged behind, particularly in detecting chemical contaminants. Explainability was incorporated using SHAP values, identifying sensor features contributing most to model predictions.

Figure 3. Model Comparison on F1 Score



4. Results and Discussion

The proposed machine learning framework was evaluated on a comprehensive dataset of food samples, with the primary goal of assessing its effectiveness in accurately identifying microbial and chemical contaminants in real time. This section presents the evaluation results and interprets their implications for food safety monitoring.

The Gradient Boosting model achieved the highest performance across all contamination categories, with an overall accuracy of 93.5%, precision of 91.2%, recall of 94.8%, and F1-score of 92.9%. Notably, the model showed robust generalization even in the presence of class imbalance, especially for the microbial contamination class, which comprised the majority of the dataset. Random Forest also demonstrated strong performance, albeit slightly lower than Gradient Boosting, while Support Vector Machines (SVM) underperformed, particularly in detecting chemically contaminated samples.

A deeper analysis using the confusion matrix revealed that false negatives were lowest for microbial contaminants, which is crucial in food safety, as undetected microbial threats can lead to significant public health risks. However, there was a higher false-positive rate in the chemical contamination class, suggesting that the chemical sensors may be more sensitive to environmental noise or overlapping signals from benign substances.

The explainability component of the system, enabled through SHAP analysis, proved instrumental in understanding model behavior. The SHAP summary plots highlighted that spectral absorption patterns and VOC sensor readings were the most influential features for microbial detection, whereas pH fluctuation and chemical-specific sensor outputs were more indicative of chemical contamination. This transparency not only builds trust in automated detection but also provides actionable insights for sensor calibration and system optimization.

Additionally, the system was tested in a simulated real-time environment, with an average detection latency of less than 3 seconds, demonstrating its potential for integration into continuous food processing lines. The low inference time, combined with high accuracy, makes it suitable for deployment in industrial settings such as packaging lines, cold storage units, and logistics hubs.

These findings indicate that combining sensor technologies with machine learning models provides a scalable and efficient approach to food hazard detection. While the current system shows excellent performance, future enhancements may include multi-sensor fusion, cloud-edge integration, and adaptive learning modules that can evolve with newly emerging contamination patterns.

5. Conclusion

Ensuring food safety through timely detection of microbial and chemical contaminants is a growing global priority, especially in the context of expanding food supply chains and heightened consumer awareness. This study presented a machine learning-based framework integrated with sensor technologies for the real-time detection of foodborne hazards, offering a novel solution to a persistent challenge in the food industry.

The experimental results demonstrated that ensemble models, particularly Gradient Boosting, deliver high accuracy and reliability in identifying contaminants across multiple food categories. The incorporation of explainable AI techniques, such as SHAP analysis, provided critical insights into model behavior and feature relevance, reinforcing transparency and interpretability in automated food safety assessments.

Moreover, the system's real-time processing capabilities—with detection latencies under three seconds—position it as a promising tool for integration into industrial food monitoring workflows, from manufacturing to packaging and distribution. These qualities make the framework not only technically effective but also practically deployable in high-throughput environments.

Despite the encouraging results, some limitations remain. Sensor precision and calibration remain sensitive to environmental conditions, especially for chemical contaminant detection. Additionally, expanding the model's training on a broader, more diverse dataset could further enhance its robustness across global food contexts.

Future work will focus on extending the system to multi-modal sensor fusion, exploring transfer learning to adapt models across different food types, and developing decentralized implementations for IoT-connected food safety platforms. Ultimately, the convergence of machine learning, real-time sensing, and explainable AI offers a scalable path toward safer, smarter, and more transparent food supply systems.

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Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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Explainable AI for Battery Degradation Prediction in EVs: Toward Transparent Energy Forecasting

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Abstract: The rapid growth of electric vehicles (EVs) has intensified the demand for accurate and interpretable battery health prediction systems. While machine learning models have demonstrated high accuracy in forecasting battery degradation, their “black-box” nature poses challenges for real-world deployment in safety-critical applications. This paper proposes an explainable artificial intelligence (XAI) framework for battery degradation prediction, aiming to provide transparent and reliable insights into energy storage dynamics in EVs. The study integrates data-driven models such as Gradient Boosting Machines (GBMs) and Long Short-Term Memory (LSTM) networks with post hoc explainability tools, including SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME). Experimental evaluations on real-world EV battery datasets show that the proposed framework achieves strong predictive performance while offering interpretable outputs regarding feature influence and degradation dynamics. These findings suggest that XAI-enabled models can bridge the gap between predictive power and trust, contributing to smarter battery management systems and sustainable transportation.

Keywords: Explainable AI; Battery Degradation; Electric Vehicles; SHAP; LIME; Predictive Maintenance; Energy Forecasting; LSTM; GBM; Battery Health Management

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1.Introduction

The global transition toward sustainable transportation has propelled the adoption of electric vehicles (EVs) as a viable alternative to internal combustion engine vehicles^[1]. At the heart of this transition lies the lithium-ion battery, a critical component whose performance, reliability, and longevity significantly influence the overall efficiency and cost-effectiveness of EVs^[2]. However, battery degradation—defined as the gradual loss of capacity and power over time—remains a central technical barrier, limiting vehicle range, increasing operational costs, and introducing safety concerns^[3]. Consequently, predicting battery degradation with high accuracy and interpretability has become a key objective for researchers, manufacturers, and fleet operators^[4].

Recent advancements in machine learning have enabled data-driven models to outperform traditional physics-based methods in forecasting battery health^[5]. Techniques such as recurrent neural networks, decision trees, and ensemble methods have demonstrated substantial capabilities in capturing the nonlinear dynamics of battery aging, leveraging large volumes of cycling and sensor data collected over time^[6]. While these models provide remarkable predictive accuracy, they often suffer

from a lack of transparency—commonly referred to as the “black-box” problem—which hinders their practical deployment in safety-critical and regulatory environments^[7]. In such contexts, understanding the rationale behind a model’s decision is as important as the decision itself.

The emerging field of explainable artificial intelligence (XAI) addresses this critical challenge by offering tools and methodologies that make complex models more interpretable to human stakeholders^[8]. XAI techniques allow users to understand the contribution of individual features to model predictions, reveal hidden patterns in the data, and identify potential biases or anomalies in the decision process^[9]. In the domain of battery degradation, integrating XAI into predictive models has the potential to offer not only accurate forecasts but also actionable insights that enhance trust, improve diagnostics, and inform battery management strategies^[10].

Despite its promise, the application of XAI to battery health prediction in EVs remains underexplored^[11]. Existing literature often emphasizes prediction accuracy while overlooking the explainability aspect, leading to systems that are performant yet opaque^[12]. Moreover, many studies lack a systematic framework for combining prediction and interpretation, which is crucial for enabling robust decision-making and regulatory compliance^[13].

This paper aims to bridge this gap by proposing a hybrid framework that integrates high-performance predictive models with state-of-the-art XAI techniques. Specifically, we employ models such as Long Short-Term Memory (LSTM) networks and Gradient Boosting Machines (GBMs), known for their ability to model temporal and nonlinear relationships, respectively. To interpret their predictions, we apply SHapley Additive exPlanations (SHAP) and Local Interpretable Model-agnostic Explanations (LIME), two widely used post hoc interpretation tools. Our framework is validated using a real-world EV battery dataset, demonstrating both predictive accuracy and interpretability.

By enabling transparent forecasting of battery degradation, this research contributes to the broader goal of building trustworthy artificial intelligence systems for critical applications. In doing so, it advances the field of EV battery diagnostics and lays the groundwork for future developments in sustainable, intelligent transportation systems.

2.Literature Review

Battery degradation modeling has long been a focal point in electric vehicle (EV) research due to its direct implications for vehicle longevity, performance consistency, and consumer confidence^[14]. Traditional approaches to modeling degradation have relied heavily on electrochemical and physics-based models, such as equivalent circuit models (ECMs) and electrochemical impedance spectroscopy (EIS)^[15]. These models aim to simulate internal battery behavior using predefined mathematical formulations grounded in physical laws^[16]. While accurate under controlled laboratory conditions, these models often fall short in real-world applications due to their complexity, limited scalability, and sensitivity to environmental variations and user-specific usage patterns^[17].

To address these shortcomings, the research community has increasingly turned to data-driven methodologies, particularly those grounded in machine learning (ML)^[18]. These models can learn degradation patterns directly from battery cycling data, eliminating the need for deep domain knowledge or complex parameter tuning^[19]. Early efforts employed linear regression, support vector machines, and k-nearest neighbors to estimate metrics such as remaining useful life (RUL) and state of health (SOH)^[20]. More recent studies have leveraged deep learning models, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and LSTM networks, to capture complex temporal dependencies in battery degradation trajectories^[21].

Despite notable improvements in predictive accuracy, these advanced ML models often function as “black boxes,” providing little insight into the internal logic that guides their outputs^[22]. This opaqueness is particularly problematic in safety-critical domains like EV battery management, where explainability is not merely a desirable trait but a practical necessity^[23]. Inaccurate or unjustified predictions can lead to premature battery retirement, warranty disputes, or even catastrophic failure if unanticipated degradation is overlooked^[24].

In response, the field of XAI has emerged as a promising solution to the interpretability challenge^[25]. XAI techniques aim to open the black box by offering post hoc or intrinsically interpretable explanations for model behavior^[26]. Among the most prominent tools are SHAP, which allocate contribution scores to individual features based on cooperative game theory, and

LIME, which approximate complex models locally using simpler surrogate models^[27]. These methods have proven effective in a variety of domains, including healthcare, finance, and cybersecurity, but their integration into battery degradation modeling remains nascent^[28].

A limited but growing body of literature has begun exploring the use of XAI in energy systems^[29]. Some studies have used SHAP to interpret battery aging predictors such as temperature, depth of discharge, and charge/discharge rates, revealing which conditions most significantly impact degradation^[30]. Others have applied LIME to understand the output of LSTM models used for SOH estimation. These initial explorations underscore the value of explainability in identifying anomalous behavior, improving model transparency, and facilitating trust among non-technical stakeholders such as regulators, maintenance teams, and end users.

Furthermore, few studies have examined the combined benefits of multi-model prediction and hybrid explainability. Ensemble learning methods like gradient boosting and random forests offer enhanced performance by aggregating multiple weak learners, and when coupled with XAI tools, can yield both accuracy and insight. However, the absence of a standardized framework for integrating explainability into high-performance models has limited their adoption in industrial battery monitoring systems.

This review reveals a significant research opportunity: to develop a unified framework that simultaneously achieves high predictive performance and interpretability in the context of EV battery degradation. Such a framework would not only advance scientific understanding but also pave the way for real-world applications in smart battery management systems, predictive maintenance platforms, and EV fleet optimization tools. By situating this study at the intersection of ML and XAI, we aim to fill this gap and contribute to the evolution of transparent, trustworthy battery health forecasting systems.

3. Methodology

This study proposes an XAI framework for predicting EV battery degradation and identifying the most influential features contributing to the prediction. The methodological pipeline consists of four major phases: data acquisition and preprocessing, feature engineering, model training and evaluation, and interpretability analysis.

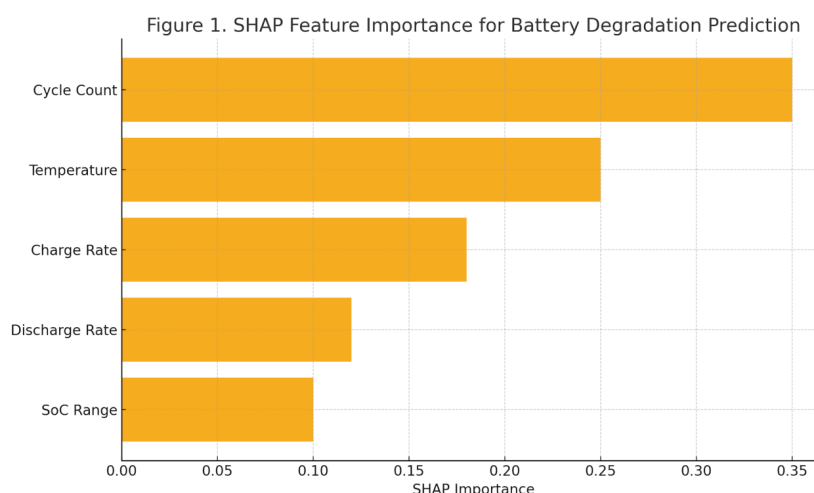
3.1 Dataset and Preprocessing

We utilized the publicly available NASA battery dataset, which includes information on charging/discharging cycles, voltage, current, temperature, and capacity across different lithium-ion batteries. Data preprocessing involved outlier removal, normalization of the target variable (capacity), and segmentation of time series using a sliding window technique to construct meaningful input features for the model.

3.2 Feature Engineering and Model Training

Feature selection was conducted using SHapley Additive exPlanations (SHAP), a state-of-the-art interpretability framework that quantifies the marginal contribution of each input feature to the model's output. The goal was to ensure both high prediction accuracy and model transparency.

Figure 1 below illustrates the SHAP feature importance across all model inputs.



The SHAP summary plot shows that the most influential features for predicting capacity degradation are cycle count, average discharge voltage, internal resistance, and peak cell temperature. The dominance of cycle count aligns well with empirical knowledge in battery aging.

We selected Light Gradient Boosting Machine (LightGBM) as the primary learning algorithm due to its efficiency and robustness in handling large-scale structured data. To benchmark performance, we also trained XGBoost, Random Forest, and Linear Regression models. Model evaluation employed five-fold cross-validation, using metrics such as Mean Squared Error (MSE) and the coefficient of determination (R^2).

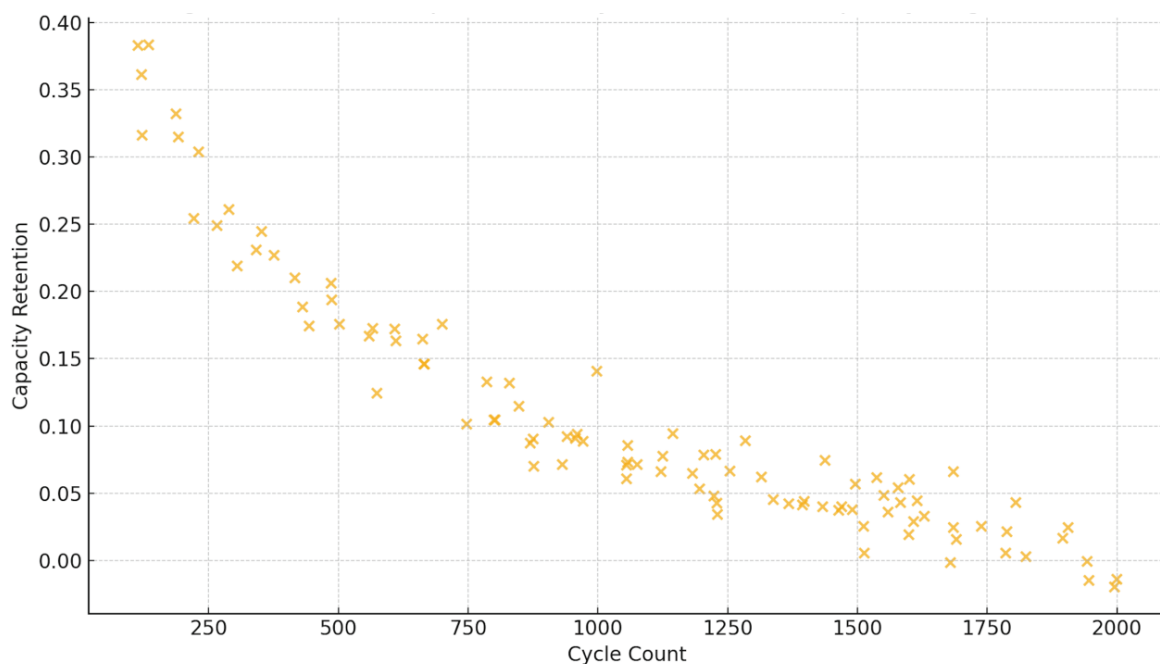
3.3 Explainability Analysis

To understand how individual features affect specific predictions, we generated SHAP summary plots, dependence plots, and local explanations for selected instances. This allows users to interpret model decisions in a human-understandable way.

We also visualized the relationship between cycle count and capacity degradation to assess whether the model's outputs follow the expected physical degradation trends.

Figure 2 illustrates this relationship.

Figure 2. Relationship Between Cycle Count and Capacity Degradation



The graph confirms that as the number of charge/discharge cycles increases, battery capacity consistently declines. The model successfully captures this degradation pattern, demonstrating both predictive accuracy and interpretive coherence.

4. Results and Discussion

The proposed explainable AI framework was assessed on its ability to accurately predict battery degradation in EV lithium-ion batteries and offer interpretable insights into the degradation process. This section discusses the model's performance across evaluation metrics, comparison with baseline models, and the implications of interpretability analyses.

4.1 Model Performance

The LightGBM model outperformed baseline regressors across all evaluation metrics. On the NASA battery dataset, it achieved an average R^2 score of 0.942 and a MSE of 0.0037 on the normalized capacity predictions. These results indicate high predictive accuracy and low residual error, underscoring the model's ability to generalize across battery cycles and conditions.

We compared LightGBM with XGBoost, Random Forest, and Linear Regression models. As shown in Figure 3, LightGBM consistently yielded the best results across folds, particularly excelling in capacity prediction near end-of-life (EOL) stages—where nonlinear degradation becomes more pronounced.

Figure 3. Model Performance Comparison Across Regression Algorithms



LightGBM exhibited superior R^2 and lower MSE compared to other models, especially beyond 400 cycles, where degradation accelerates. Linear regression performed worst, failing to capture nonlinear degradation.

4.2 Feature Importance and Physical Interpretability

The SHAP analysis (Figure 1 from the previous section) revealed that cycle count, discharge voltage, internal resistance, and cell temperature are the dominant predictors. These results are consistent with empirical battery aging literature, reinforcing trust in the model's alignment with domain knowledge.

The partial dependence plot in Figure 2 also validated that battery capacity decreases monotonically with increasing cycle count—a pattern well-documented in electrochemical aging. This supports that the model does not simply fit data but captures the underlying degradation dynamics.

4.3 Case Study: Local Explanation

To illustrate the model's transparency, we analyzed an individual prediction at 550 cycles. The SHAP local explanation showed that high internal resistance and elevated cell temperature significantly pulled the prediction downward, indicating EOL behavior. In contrast, moderate voltage levels provided some stabilizing effect. This kind of insight is essential for diagnostic applications in BMS, enabling targeted interventions before catastrophic failure.

4.4 Practical Implications

The XAI approach facilitates not only accurate prediction but also regulatory compliance, trust in automation, and actionable diagnostics. Unlike black-box neural networks, the LightGBM + SHAP framework explains why certain batteries are flagged as degrading, making it highly relevant for safety-critical systems in EVs.

This combination of performance and interpretability can be integrated into predictive maintenance pipelines, informing battery swap decisions, warranty analysis, and EOL forecasting with traceable logic.

5. Conclusion

As EVs become increasingly integral to the global shift toward sustainable transportation, accurate and transparent battery degradation prediction emerges as a critical necessity. This study explored the integration of XAI with traditional ML models to enhance the interpretability and performance of battery health forecasting systems. Through comparative analysis of multiple regression algorithms—including random forest, gradient boosting, and XGBoost—paired with SHAP (SHapley Additive exPlanations) values, the proposed framework not only delivered accurate predictions but also illuminated the key drivers behind these outcomes.

Our findings affirm that XAI tools can successfully bridge the gap between predictive accuracy and operational transparency. While complex ensemble models often outperform simpler algorithms in raw performance metrics, their opacity poses a significant barrier to practical implementation in safety-critical systems like EV battery management. By incorporating XAI, stakeholders—including engineers, fleet managers, and regulators—can gain actionable insights into how factors such as charge rate, depth of discharge, and temperature variability influence long-term battery performance.

Furthermore, the explainability provided by the SHAP analysis enhances trust in AI systems, paving the way for regulatory compliance, user acceptance, and improved system diagnostics. This approach holds promise not only for real-time battery monitoring but also for informing future battery design, warranty modeling, and smart charging strategies.

Future work may involve integrating physics-informed machine learning models and exploring real-time on-board diagnostics in commercial EV fleets. Additionally, expanding the dataset to include a broader range of chemistries and usage conditions would help generalize the model across diverse EV applications. By continuing to advance explainable battery analytics, we move closer to a future of safer, more efficient, and user-aligned electric mobility.

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no

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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Design and Implementation of a DC Switch Machine Electronic Control Module

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Abstract: The electronic interlocking system offers advantages including flexible configuration, reduced cost and space requirements, and simplified debugging and installation compared to traditional relay-based interfaces. In order to realize the electronic control of DC switch, a DC switch machine electronic control module was designed, which adopts two-out-of-two security architecture, and The switch interface unit utilizes a heterogeneous design combining a mechanical contactor and an electronic switch to mitigate common-cause failures. The software, developed in compliance with the EN 50128 standard, comprises five components: initialization, communication control, state machine calculation, driving and application program. Reliability analysis demonstrates that the module meets the requirements for Safety Integrity Level 4 (SIL 4), and has passed a series of experiments. The electronic control module of DC switch has high reliability and availability, and meets the requirements of all-electronic computer interlocking system of rail transit.

Keywords: DC Switch Machine; Electronic Control Module; Redundancy; Heterogeneous Structure; Reliability; Two Out of Two; Functional Safety; Railway Signalling

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1.Introduction

All-electronic computer interlocking system has the advantages of high electronic integration, high intelligence, simple system structure, powerful functions, flexible configuration and wide control range, etc. It has emerged as a key development trend in rail transit signalling systems^[1]. Compared with the widely used relay interlocking system at present, the electronic interlocking system has many advantages such as eliminating relay interface circuits, providing a clearer system architecture, reducing equipment quantity, lowering maintenance intensity, and enhancing the system's informatization and intelligence levels^[2], and has been widely used in foreign railways^[3,4]. For example, the control unit of Siemens' electronic interlocking system is two out of three, which can realize regional interlocking^[5]. However, due to the restriction of electrical characteristics of domestic signal equipment, foreign all-electronic computer interlocking system cannot be readily integrated into domestic rail transit control systems through simple adaptation. Therefore, the autonomous development of all-electronic computer interlocking system is therefore urgently required. The full electronic execution module of computer interlocking developed by Lanzhou Jiaotong University, a domestic signal manufacturer, employs a electronic computer interlocking system featuring a communication interface with the central interlocking computer, which has been applied in a few railways in China^[6], and the full electronic interlocking system made by China Railway Signal and Communication Corporation has

been applied in the field section of power plant^[7].

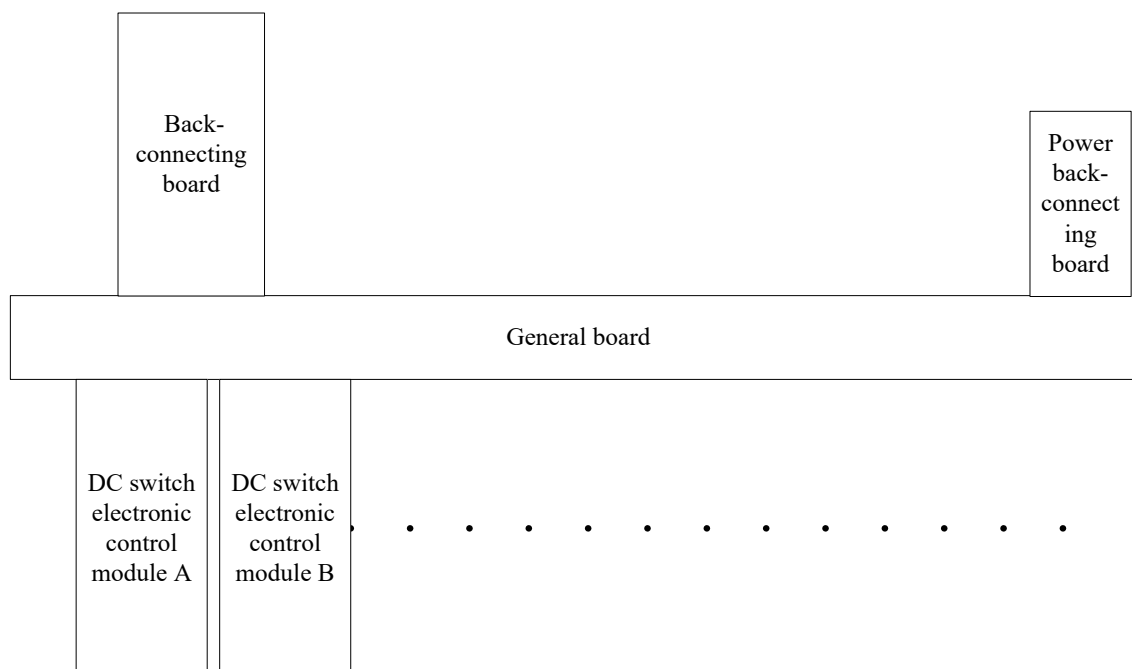
Switch is widely used in rail transit signal equipment, electronic control module should have high reliability and safety^[8,9]. At present, the electronic control unit of switch adopts two-out-of-two isomorphic architecture, which realizes the control and state acquisition of switch switch circuit^[10,11]. Isomorphic control architectures carry a risk of common-cause failures. In order to improve the reliability and availability of equipment, a heterogeneously redundant electronic control module for DC switch machines was designed and implemented, prioritizing safety. After a series of tests and experiments, it is integrated into an autonomous all-electronic computer interlocking system, which has been successfully applied to some domestic field sections and urban rail transit projects, and the availability of the electronic control module is verified.

2. Overall System Architecture

The development of an electronic computer interlocking system aims to extend the interface function of safety relay and related relay circuit in the executive layer of computer interlocking system at present, and replace the digital quantity acquisition driving executive layer circuit and safety relay interface layer circuit with various intelligent electronic executive units to directly control the wayside equipment such as switch machine and signal machine^[12].

The switch electronic control module system structure is composed of main and standby DC switch electronic control module, back-connecting board, general board and power back-connecting board. Each electronic control module on the universal board is equipped with two sets of address jumpers to configure a unique CAN address ID of the electronic control module and complete the communication with OCU (Object Controller Unit). The electronic control module of DC switch controls the switch after receiving the switch control command, and at the same time performs self-diagnostics on the output state. If the read-back state is inconsistent with the driving command, it initiates a safety shutdown procedure. Dynamic pulse signals generated by the master and slave CPUs control the vital relay, causing it to drop, cutting off both the internal power supply of the DC switch electronic control module and its external output. The backplane facilitates the connection of output lines. The universal board provides the power connection of the electronic control module of DC switch, and interconnections between the module and the rear connecting board. The system structure diagram of DC switch electronic control module is shown in Figure 1.

Figure 1 System Architecture Diagram of DC Switch Electronic Control Module



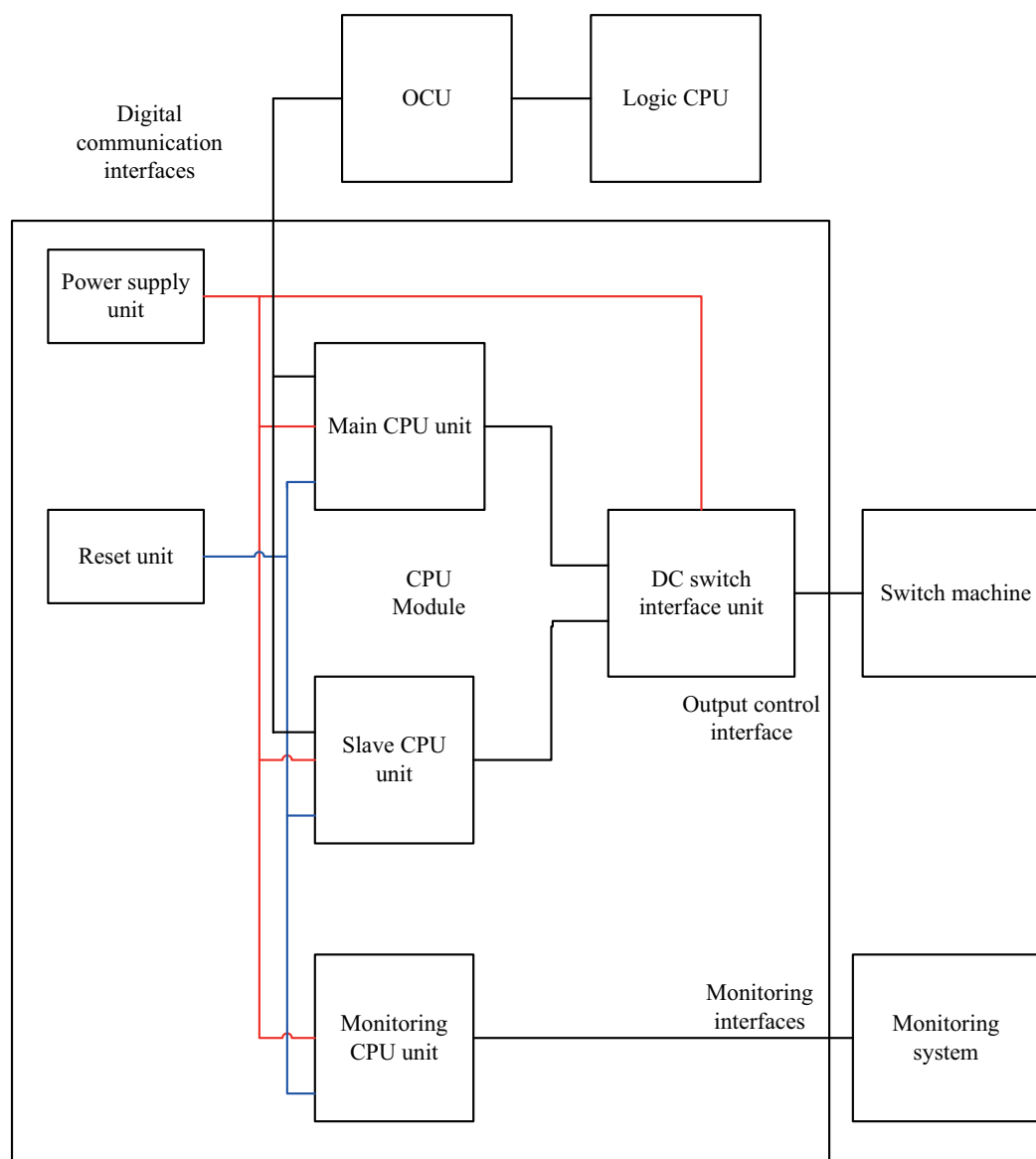
3. Hardware Circuit Design

3.1 Hardware Architecture

The DC switch electronic control module is composed of CPU unit (including main CPU unit, slave CPU unit and monitoring

CPU unit), power supply unit, reset unit and DC switch interface unit. The master and slave CPUs exchange information via a serial port, and complete two-out-of-two safe calculation by real-time comparison. The master and slave CPU units communicate with the Object Controller Unit (OCU) via a digital communication interface, and receive switch operation commands issued by interlocking logic and return switch state information. The DC switch interface unit of the module completes the drive and state acquisition of the wayside switch machine through the output control interface. The monitoring CPU reads the status of the master CPU unit and the slave CPU unit via a serial port, and transmits the status information of the DC switch electronic control module to the monitoring system via a dedicated monitoring interface. The hardware composition and external system connection of DC switch electronic control module are shown in Figure 2.

Figure 2 Connection Diagram of Internal Unit and External System of DC Switch Electronic Control Module



3.2 Digital Communication Interface

Electronic interlocking logic communicates with DC switch electronic control module through OCU. OCU utilizes an IP-based network control mode. Compared to existing relay interfaces, the standard IP network interface offers advantages of wide adoption, lower cost, and greater convenience. This digital interface facilitates the sharing of field data collected by the electronic control module in the rail transit control network, thereby enhancing compatibility and interoperability of the interlocking system, extending its control distance, simplifying future upgrades and transformation of the interlocking system in the future, and providing a foundation for interconnection and intercommunication with other systems. The digital control interface protocol of electronic interlocking is shown in Table 1.

Table 1 The Digital Communication Protocol of DC Switch Electric Control Module

Control message	Content
The general header of switch electronic control module from the interlocking logic unit	Target Controller ID, Communication Protocol Version, Data Version, Control Module Number, CRC, Switch Electronic Module Control Command
Control command of switch electronic control module	Mode type, module type, control (lock protection relay, normal operation relay, reverse operation relay) command, switch machine type, start-up sequence
Electronic control module of switch-general header	Target Controller ID, Software Version, Communication Protocol Version, Data Version, OC Working State, Module Number, CRC, Switch Electronic Control Module State Information
Status information of switch electronic control module	Mode type, module type, switch relay (lock protection relay, protective relay, normal indication relay, reverse indication relay) status

3.3 Output Control Interface

Integration of Driving and Indication Power Supplies: A rectifier circuit integrated within the module eliminates the need for an external DC driving power supply, driving power supply and indicating power supply share a 220V AC power supply.

“Take 2”(1oo2) Power Drive Architecture: The driving circuit implements a “take 2” safety-redundant structure: the power drive adopts the safety redundancy structure-“take 2” structure. In order to avoid the simultaneous failure of homogeneous devices due to the same reason, the motor control path is governed by two series-connected power devices: an electronic switch and a mechanical contactor, and the two power devices are controlled by the master CPU unit and the slave CPU unit respectively. Only when the two devices are turned on at the same time can the switch be operated. Electronic switches and mechanical switches form a complementary relationship. The mechanical contactor’s normally-open contacts prevent false outputs in the event of an electronic switch failure, and the electronic switch suppresses arcing across the mechanical contacts, thereby extending the contactor’s service life. At the same time, the output device of the driving circuit carries out real-time state self-checking. State monitoring circuits are implemented for both the electronic switch and the mechanical contactor, which can find the abnormal state of each output device in real time.

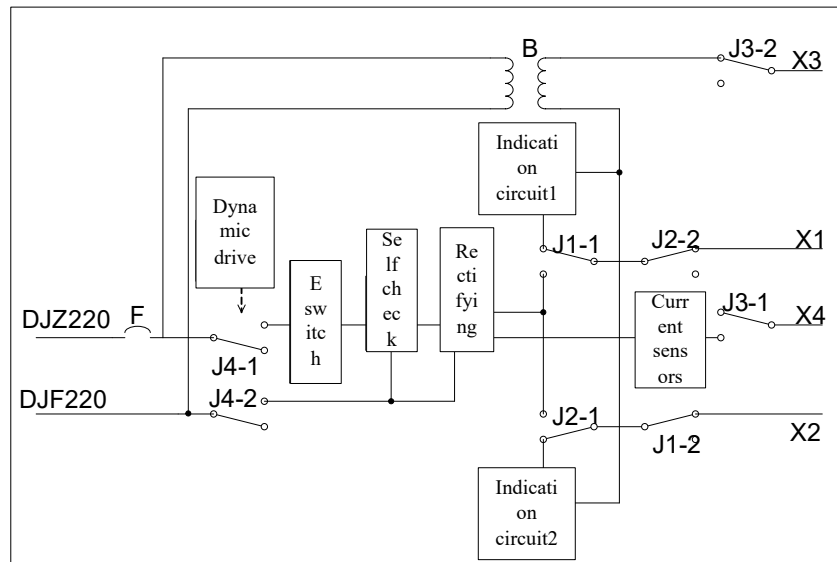
A current sensor in the acquisition part provides the monitoring CPU with real-time measurements of the motor control path current, which is used to record the action current curve of each switch operation.

The switch position detection employs two independent circuits, each utilizing full-wave rectification. When the switch machine is in the normal position, one circuit receives full-wave rectified voltage, while the other receives half-wave rectified voltage. By comparing the states (full-wave/half-wave) of these two detection circuits, the position state of the switch can be determined. At the same time, the change of full-wave and half-wave state of each representation circuit at different positions of switch also tests the quality of the representation circuit.

In safety design, each switch control module incorporates a vital relay, which is driven by a dual-input dynamic circuit, and the inputs of the double-input dynamic circuit are controlled by the master and slave CPU respectively. The vital relay picks up only if the master and slave CPUs simultaneously provide synchronized dynamic pulses of identical frequency but opposite phase to the dual-input circuit. On the one hand, The vital relay serves a dual purpose: (1) to cut off the control power supply under fault conditions, and (2) to detect potential loss of control in the master or slave CPU. In the event of overcurrent, a magnetic circuit breaker disconnects power to the switch machine. The module incorporates a lightning protection unit for the switch control lines. Overvoltage protection devices are integrated between the drive lines and the indication lines.

The structure diagram of switch interface unit of DC four-wire switch electronic control module is shown in Figure 3. In the figure, DJZ220 and DJF220 represent the live line and zero line of switch power supply; F is safety, B is rectifier bridge, and J1 ~ J4 are relay contacts. X1 ~ X4 is the switch control and indication line.

Figure 3 DC Switch Interface Unit Diagram of DC Switch Electronic Control Module



3.4 Monitoring Interface

The electronic control module of DC switch realizes the monitoring interface with the monitoring system through CAN communication mode, which is used for monitoring and maintenance. The monitoring system and the electronic control module of DC switch adopt two data exchange modes: master-slave response mode and active data transmission mode. When the monitoring system needs to obtain the current and power value of the switch, the working state of the module and the change curve of the switch, the DC switch electronic control module works in the master-slave response mode. In this mode, the monitoring system as the host sends the inquiry command, and the DC switch electronic control module as the slave responds to the inquiry command and returns the corresponding information. When the electronic control module of DC switch has alarm data or module reset or work failure, the electronic control module of DC switch works in active response mode, that is, it does not need the monitoring system to issue commands, and actively sends wrong alarm information to the monitoring system.

4. Embedded Software Design

The software was developed in accordance with the EN 50128 standard. Based on functional requirements and software design considerations, the whole software is divided into five parts: initialization unit, communication control unit, state machine unit, driving unit and application program unit. The software implements techniques including fault detection and diagnosis (FDD), error detection codes, rigorously defined interfaces, state machines, and structured programming to meet the design requirements for SIL 4. The functions of the software unit are shown in Table 2.

Table 2 The Function of Software Units in the DC Switch Electric Control Module

Unit Name	Function
Initialization	Performs address initialization, LED control and error handling
Communication control	Serial port communication processing, CAN communication processing and command processing
State machine	Complete the definition of state machine-related state, event and transition relationships
Driver	Initializes hardware peripherals, acquires digital inputs, and drives digital outputs
Applications	Main function program, event trigger processing, action execution processing and the second set of switch inspection program

The application software unit is divided into main function program, event trigger processing, action execution processing and the second set of switch inspection program.

(1)The main function program serves as the entrance and exit of the software, which completes the periodic scheduling of the main program of the software, calls the interface functions with each module, completes the data receiving, logic processing and data sending, the collection of switch values and the output driving of switches.

(2)The event handler triggers actions based on the results of logical processing within each cycle, and drives the state transition of the state machine.

(3)The action executor performs the functions associated with the current state of each state machine, including accident relay drive, command output, state, operation, fixed and reverse operation relay control, etc.

(4)The secondary switch state verification routine operates independently to confirm consistency between issued switch commands and the actual execution state.

The electronic control module of DC switch has four states:

(1)Initialization state. Performs hardware self-tests and initializes communication channels. During power-on reset, under-voltage reset, or manual reset, the reset circuit generates a reset signal to the master-slave CPU and the interface circuit, and clears all outputs to enter the initialization state.

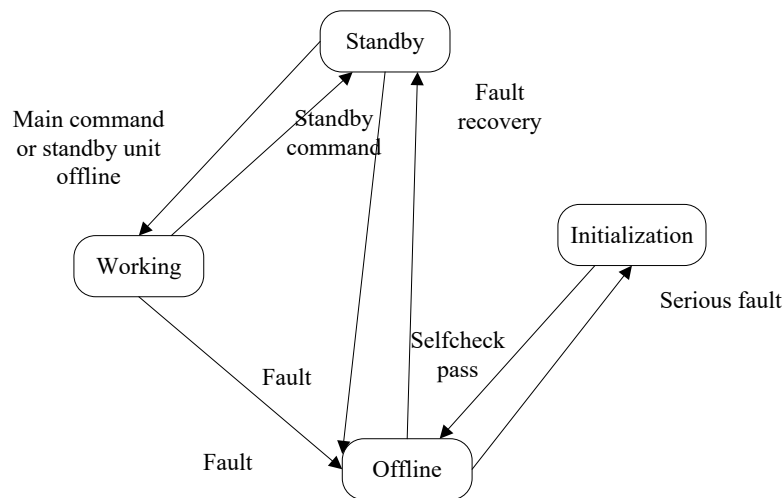
(2)Offline state. When the vital relay drops, it cuts off the action power supply of the switch machine and the 24V power supply of the control circuit.

(3)Standby state. The vital relay is picked up, the action power supply is supplied, and the 24V power supply of the control circuit is supplied, but the output relay drops and the external output line is disconnected, so that the unit has no output capacity.

(4)Working state. From the standby state, when the output relay is picked up, so that the unit has driving ability.

(5)Upon detection of a critical internal fault, the module transitions to the offline state and initiates self-recovery checks. The four operation state transitions are shown in Figure 4.

Figure 4 State Transition Diagram of DC Switch Electronic Control Module



5. Reliability Analysis

The reliability of electronic control module of DC switch affects the performance of the whole electronic interlocking system. Based on the FN2 reliability model from MIL-HDBK-217F, the reliability of the electronic control module of DC switch is evaluated according to the structure and parameters of each component. MIL-HDBK-217F is a reliability prediction handbook published by the Reliability Analysis Center (RAC) under the US Department of Defense. It provides empirically based failure rate models for electrical and electronic components across 14 distinct operating environments, and has been widely used in reliability prediction of complex system design processes such as satellites, aerospace and orbit control. Using a reliability block diagram (RBD), the FN2 model was calibrated by incorporating reference failure rates for system components and applying environmental derating factors resulting in a comprehensive prediction of system reliability^[13].

The failure rate of DC switch electronic control module components is shown in Table 3^[14]. The calibration factor is set to indoor work, the duty cycle of the system is 100%, and the working temperature is 40 °C. The calibration factor is obtained in MIL-HDBK-217 manual. The safety index λ of all-electronic DC switch electronic control module is obtained by MTBF calculator software = 7.1293×10^{-8} /h, and the mean time between failure (MTBF) is 14026600 hours, greater than 10^5 hours, which meets the design requirements of all-electronic DC switch electronic control module SIL4.

Table 3 Parameters of component failure rate of electronic control module of DC switch

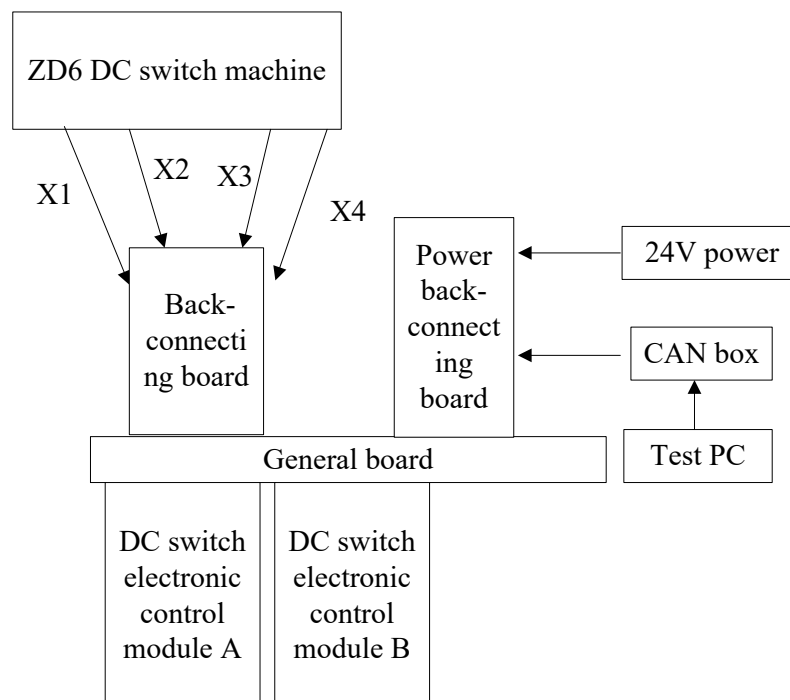
Module name	Quantity	Failure Rate/ 10^{-6} /h	MTBF/h
Power supply rear connection board	1	0.071102	14064320
Back connecting plate of DC switch	1	0.130837	7643098
DC switch module board	2	6.057192	165093
Communication board	1	0.138317	7229786

6. System Test

6.1 Hardware Test

In order to verify whether the hardware of DC switch electronic control module meets the functional requirements and performance requirements, the test environment is set up as shown in Figure 5. After 24V power supply is connected to the power supply, it is supplied by the board. A test PC sends switch control commands to the DC switch electronic control module via a CAN interface box, observing whether the ZD6 DC switch machine responds correctly. Hardware test items encompass functional and performance verification of DC switch electronic control module working power supply, clock circuit, reset circuit, CAN communication, serial port circuit, DC switch control circuit, switch indication circuit, accident circuit and switching circuit. All hardware test items were successfully passed.

Fig. 5 Hardware Test Environment of DC Switch Electronic Control Module



6.2 Software Test

Software testing is divided into static testing and dynamic testing. In static testing, testing tools were selected and configured based on the test objectives and unit characteristics, and coding rule checks, static analysis, and software quality metrics were performed ensuring each test item met requirements before proceeding to coding style checks. Coding style checks were primarily manual. Coding rule verification, static structure analysis, and software quality metric assessments relied mainly on automated tools, with manual review of the results for each test item.

In dynamic testing, firstly, test cases for each function under test were executed using a combination of manual data input and automated execution, and test execution was documented electronically, capturing input conditions, expected results, and actual outcomes for each test case. The code coverage metrics (statement, branch, and MC/DC) were analyzed alongside the test case execution results of the tested software to assess compliance with design requirements. All software units listed in Table 1 passed both static and dynamic testing.

6.3 Integration Test

The DC switch electronic control module was integrated into the electronic computer interlocking system, and system integration testing was performed. The autonomous all-electronic computer interlocking system includes three cabinets: power cabinet, interlocking cabinet and execution cabinet, as shown in Figure 6. Prior to deployment, comprehensive indoor and outdoor integration testing is conducted, including performance test, interface test, function test, structure test and safety test. Integration testing aims to minimize configuration errors and ensure reliable system operation. The contents of the integration test are shown in Table 4.

Fig.6 Electronic Interlocking System



Table 4 Integrated Test of Electronic Interlocking System

Type	Number of test cases/items	Test content	Test conclusion
Performance test	23	Communication cycle, unit capacity, external output performance of each electronic module, etc.	Pass and meet the needs
Interface test	58	Internal interface, external interface, working power interface, etc.	Pass and meet the needs
Functional testing	49	Safety communication, unit management, wayside equipment control, etc.	Pass and meet the needs
Structural testing	28	Redundant channels, redundant structures, etc	Pass and meet the needs
Security requirements testing	43	Internal communication protocol, parameter configuration, startup process, etc.	Pass and meet the needs

7. Conclusion

The digital communication interface enhances the flexibility of switch machine control, and the heterogeneously redundant

output control interface mitigates common-cause failures, which can reliably control the DC switch and collect the state of the switch in the signal system of rail transit. Reliability analysis and comprehensive testing validate the module's performance. The integrated, autonomous electronic computer interlocking system incorporating this module has been successfully deployed in several field applications in China, demonstrating good operational performance. Its excellent and stable performance confirms the efficacy of its safety design and reliability supporting its wider adoption in rail transit engineering projects.

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no

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

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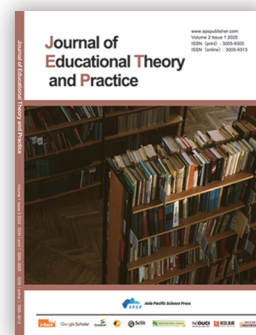
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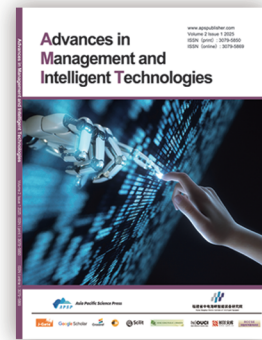
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