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Intelligent Monitoring and Fault Early Warning for Automotive Production Line Equipment Based on Neural Network

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Abstract: *With the continuous advancement of industrial intelligence, the requirements for the stable operation of automotive production line equipment are becoming increasingly higher. Addressing the shortcomings of traditional fault warning methods, such as poor real-time performance and low accuracy, this paper takes the H automotive intelligent assembly production line as the research object. It designs an intelligent monitoring and fault early warning system for automotive production line equipment based on a sensor network, neural network clustering analysis, and a Least Squares Support Vector Machine (LS-SVM) regression model. By collecting and analyzing equipment operational data in real-time, the system improves fault warning accuracy and shortens warning response time, providing effective technical support for automotive intelligent manufacturing.*

Keywords: *Neural Network; Fault Early Warning; Intelligent Monitoring; Support Vector Machine (SVM); Predictive Maintenance*

1. Introduction

Modern automotive manufacturing production lines are highly intelligent industrial production systems. Equipment reliability is directly related to production efficiency and economic benefits. traditional maintenance methods struggle to meet the requirements for equipment reliability in modern intelligent manufacturing. Following the widespread adoption of IoT sensing technology, the methods for collecting industrial equipment operational data have undergone a revolutionary change. High-frequency sensors have sampling rates up to the millisecond level, with a single device generating tens of GB of data daily[1] . This explosive growth of data provides support for intelligent fault warning but also presents challenges in data processing and analysis. This paper utilizes experimental data from the H automotive assembly workshop to construct an intelligent early warning system for multi-source heterogeneous data, solving the dual bottlenecks of real-time performance and accuracy in traditional methods. It achieves a transition from reactive maintenance to predictive maintenance, providing strong technical support for the intelligent transformation and upgrading of the automotive manufacturing industry.

2. Intelligent Monitoring System Architecture and Key Technologies

2.1 System Architecture

The intelligent monitoring system adopts a hierarchical distributed architecture design, fully considering the complexity and reliability requirements of modern industrial environments. The system architecture consists of four layers: Device Layer, Edge Layer, Platform Layer, and Application Layer. Communication and control command transmission between these layers rely on standard industrial communication protocols[2].

The Device Layer deploys a large number of different types of high-precision sensors, such as vibration acceleration sensors, infrared temperature sensors, and pressure sensors, totaling 342 monitoring points, enabling comprehensive perception of the operating status of critical equipment.

The Edge Layer primarily includes three functions: firstly, localized data preprocessing, including signal filtering, noise reduction, and feature extraction; secondly, real-time data analysis for simple fault judgment and warning rules; thirdly, acting as a data buffer to ensure data integrity during network disconnections. The Edge Layer uses the OPC UA protocol to communicate with the Device Layer and industrial Ethernet to communicate with the Platform Layer.

The Platform Layer is the core processing layer of the system, deployed in an enterprise private cloud environment. It adopts a microservices architecture, using Docker containerization technology to deploy various data processing and analysis services. The Platform Layer includes multiple functional modules: the data storage module uses the time-series database InfluxDB to store massive monitoring data; the data processing module performs further data cleaning and feature engineering; the model service module runs various machine learning algorithms. The Platform Layer primarily conducts in-depth analysis and modeling on data uploaded from the Edge Layer to achieve accurate equipment status assessment and fault prediction.

The Application Layer, as the top layer of the system, provides various services to end-users. This layer includes a web monitoring interface, mobile applications, an early warning information push system, and many other components. The key role of the Application Layer is to present the analysis results from the lower layers in an intuitive form to users, providing functions such as equipment status monitoring, warning management, and maintenance decision support.[3] It interacts with the Platform Layer via RESTful APIs to ensure consistency between front-end and back-end data.

2.2 Key Technologies

2.2.1 Data Collection

The data acquisition module spans the Device Layer and the Edge Layer in the system architecture. It selects the OPC UA unified architecture protocol to ensure standardized access of data from devices of different manufacturers. To address the severe electromagnetic interference in industrial environments, the data acquisition module is designed with multiple filtering and protection circuits, ensuring a signal-to-noise ratio above 75 dB. Data transmission uses timestamp synchronization, with the maximum time error controlled within ±2 ms, thus achieving temporal consistency for multi-source data. The data preprocessing stage uses an improved sliding window Z-score standardization method:

$$X_{\text{norm}} = \frac{X - \mu_{\text{window}}}{\sigma_{\text{window}}}$$

Where μ_{window} is the mean of the data within the sliding window, and σ_{window} is the standard deviation of the data within the sliding window. By setting an adaptive window size (2-10s), data dynamics are maintained while eliminating instantaneous interference. Main Sensor Configuration Parameters are shown in Table 1.

Table 1 Main Sensor Configuration Parameters

Sensor Type	Model Specification	Sampling Frequency	Measurement Accuracy	Installation Workstation	Quantity	Communication Protocol
Vibration Accel.	PCB 608A11	10 kHz	±0.5%	Engine Assembly	128	IEPE
Infrared Temp.	Fluke 62 Max+	100 Hz	±0.5℃	Welding Robot	87	4-20mA
Pressure Sensor	Rosemount 3051	1 kHz	±0.1%	Hydraulic System	127	HART
Acoustic Emission	Physical Acoustics	500 kHz	±1dB	Transmission Test	42	USB
Current Monitor	Hioki 3286	50 Hz	±0.2%	Motor Drive	58	Modbus

2.2.2 Neural Network Feature Extraction

The neural network feature extraction module is located in the model service module of the Platform Layer. Feature extraction is a key link in the intelligent early warning system, directly affecting the accuracy of subsequent analysis. This paper designs an intelligent feature extraction architecture combining a Deep Convolutional Network and a Long Short-Term Memory (LSTM) network. This architecture leverages the strengths of CNN in spatial feature extraction and LSTM in time series modeling, achieving deep feature mining of multi-source heterogeneous data.

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The Convolutional Neural Network part uses a four-layer deep structure, each layer containing convolution operations, activation functions, and pooling operations. The convolutional layers use the ReLU activation function:

$$f(x) = \max(0, x)$$

Where $f(x)$: represents the output of the ReLU function. x: represents the input value to this activation function, generally the weighted sum from the previous layer's output.

This activation function is computationally fast and also helps alleviate the vanishing gradient problem in deep networks. The pooling layers use max pooling operation with a kernel size of 2x2 and a stride of 2, preserving main features while reducing the number of parameters. To prevent overfitting, a Dropout layer is added after each convolutional layer with a dropout rate of 0.25. The Long Short-Term Memory network part consists of three layers, each with 128 memory units. LSTM establishes long-term dependencies through gating mechanisms. The calculation formula for the forget gate is:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

Where f_t represents the output value of the forget gate at time step t, its value range is [0,1], controlling which information in the cell state will be discarded. σ represents the Sigmoid activation function, compressing the output to the (0, 1) interval. W_f represents the weight matrix associated with the forget gate. $[h_{t-1}, x_t]$ represents the concatenation of the hidden state from the previous time step h_{t-1} and the input at the current time step x_t into a vector. b_f represents the bias vector of the forget gate.

The input gate and output gate adopt similar structures, collectively controlling information flow and memory, allowing the model to capture both short-term fluctuations and long-term trend features of equipment operation.

The training process uses the Adam optimizer with an initial learning rate of 0.001, a batch size of 128, and a gradient clipping threshold set to 1.0 to prevent gradient explosion. The training data is divided into training, validation, and test sets with ratios of 70%, 15%, and 15% respectively. After 120 training epochs, an accuracy of 94.3% was achieved on the test set, and the loss function value converged to 0.086. The feature extraction effect visualized by t-SNE showed obvious clustering phenomena for data points of different states, indicating that the extracted features have good discriminative power.

2.2.3 Dynamic Clustering Analysis Algorithm

Equipment state identification is the foundation of fault warning. This paper uses an improved density clustering algorithm to automatically partition operational states. The traditional DBSCAN algorithm has shortcomings when processing industrial data, such as sensitivity to parameters and poor adaptability to density variations. Therefore, this paper proposes an adaptive clustering algorithm based on density reachability optimization.

The core of this algorithm is the dynamic selection of the neighborhood radius https://media/image16.wmf (eps) and the minimum number of samples minPts parameters. By analyzing the characteristics of the data distribution, the initial parameters are set as ε =0.35 and minPts=15. Kernel Density Estimation (KDE) is introduced to automatically adjust local parameters:

$$\hat{f}_h(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right)$$

Where h represents the bandwidth parameter, and K is the Gaussian kernel function. This adaptive mechanism enables the algorithm to effectively handle industrial data with uneven densities.

To evaluate the clustering effect, comprehensive evaluation metrics including the Silhouette Coefficient, Calinski-Harabasz Index, and Davies-Bouldin Index are used. The calculation formula for the Silhouette Coefficient is::

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$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}}$$

Where $s(i)$ represents the silhouette coefficient value for sample i, ranging between [-1, 1], with larger values indicating better clustering results. $a(i)$ represents the average distance from sample i to all other samples in its own cluster (intra-cluster dissimilarity). $b(i)$ represents the average distance from sample i to all samples in the nearest cluster (inter-cluster dissimilarity).

Experiments show that the silhouette coefficient for normal operating conditions reaches 0.82, and the accuracy rate for abnormal state detection reaches 91.5%. Using the clustering method, the equipment operating states are divided into four categories: Normal, Slight Abnormality, Severe Abnormality, and Critical Fault, providing a basis for hierarchical warning.

2.2.4 LS-SVM Regression Prediction Model

Trend prediction is an important part of fault warning. The Least Squares Support Vector Machine (LS-SVM) can be used to establish an equipment state degradation prediction model. LS-SVM uses solving linear equations instead of the quadratic programming problem in standard SVM, greatly improving computational speed, making it particularly suitable for industrial real-time scenarios. The regression model uses the Radial Basis Function (RBF) kernel:

$$K(x, x_i) = \exp\left(-\frac{\| x - x_i \|^2}{2\sigma^2}\right)$$

Where $K(x, x_i)$ represents the kernel function value between sample x and sample x_i, measuring the similarity between the samples. x represents an input feature vector. x_i represents the feature vector of the *j*-th sample in the training set. $| x - x_i |$ represents the Euclidean distance between vectors x and x_i .wmf. σ represents the width parameter of the RBF kernel function, controlling the function's range of influence and determining the smoothness of the model.

Kernel function parameter σ and the regularization parameter C are optimized using grid search combined with cross-validation. The final optimal parameter combination is: penalty parameter C=125, kernel parameter σ =0.85.

The model is trained using historical normal operation data, constructing training samples through a sliding window. Each sample contains feature data from 60 consecutive time points, and the prediction target is the state value for the next 10 time points. Incremental learning is used during training; as new monitoring data continuously joins the training set, the model can adapt to the slow changes in equipment performance[4].

3. System Implementation and Verification

3.1 Experimental Platform Setup

The verification experiment was conducted on-site at the H Automobile Third Assembly Workshop. This workshop has an annual production capacity of 150,000 vehicles and contains 356 sets of automated equipment, making it an ideal industrial validation environment. The monitoring system covers 12 key workstations across the four main process sections: stamping, welding, painting, and assembly, including important equipment such as large presses, robotic welding stations, painting robots, and assembly lines.

The hardware platform uses industrial-grade edge computing gateways (Intel Atom x7-E3950 processor, 8GB DDR4 memory) deployed near each workstation for local data preprocessing and immediate analysis. The Platform Layer is deployed on the enterprise private cloud, using Docker containerization deployment to ensure system scalability and maintainability. Data storage uses the InfluxDB time-series database, which significantly improves data query speed compared to traditional relational databases.

The data collection period was from March to August 2023, collecting a total of 2.7 TB of valid data records. This data covers various operating conditions, including normal operation, abnormal operation, and faults. Data quality assessment results showed an effective data rate of 98.2%. Missing data was filled using multiple imputation methods to ensure data integrity and reliability as much as possible.

3.2 Model Training and Optimization

The model training process adopted a phased strategy. First, offline training was conducted using historical data to establish the basic model. Afterwards, online learning was used to continuously improve the model parameters. The training data underwent strict inspection and labeling, with state labels confirmed jointly by domain experts and equipment engineers.

Special attention was paid to class imbalance during training. Using the SMOTE oversampling method combined with cost-sensitive learning improved the recognition accuracy of minority classes[5]. Model hyperparameter tuning adopted Bayesian optimization, which is more efficient compared to grid search.

The final model performed excellently on an independent test set. As shown in Table 2, compared to traditional threshold methods, a single LSTM model, and a rule-based expert system, this system increased fault warning accuracy to 92.7% and reduced the false alarm rate to 4.1%, demonstrating the model's good recognition accuracy and stability. In terms of real-time performance, the system's average response time was reduced to 3.5 minutes, significantly shorter than the traditional 25 minutes, effectively improving the system's fault response speed. System Performance Comparative Analysis is shown in Table 2.

Table 2 : System Performance Comparative Analysis

Performance Metric	Traditional Threshold Method	Single LSTM Model	Rule-Based Expert System	This System
Warning Accuracy	73.2%	85.6%	79.8%	92.7%
False Alarm Rate	18.5%	9.3%	15.2%	4.1%
Avg. Response Time	25min	8.2min	12.5min	3.5min
Prediction Lead Time	1.5h	3.8h	2.2h	6.2h
Model Training Time	-	4.5h	Manual Configuration	2.8h
Computing Resource Req.	Low	High	Medium	Medium
Interpretability	High	Low	High	Medium

4. Conclusion

In summary, the intelligent monitoring system developed in this paper utilizes multi-source data fusion and innovations in deep learning algorithms to improve the accuracy of equipment fault warnings. The comprehensive use of deep convolutional networks and long short-term memory networks leverages their respective strengths, fully utilizing the advantages of spatial feature extraction and time series modeling. The improved density clustering algorithm effectively solves the clustering problem of industrial data with uneven densities. The LS-SVM regression prediction model further improves computational efficiency while maintaining prediction accuracy.

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