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RESEARCH ARTICLE

Architecture Design and Application of IIoT Platform in Automobile Manufacturing Based on Microservices and Deep Learning Techniques

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ABSTRACT An Internet of Things (IoT) platform is a software architecture that enables the connection, management, and analysis of IoT devices, sensors, and data. It provides a centralized system for IoT devices to interact with each other and with the cloud, facilitating the collection, processing, and analysis of data from these devices. However, in the automotive manufacturing industry, traditional Internet of Things (IoT) platforms are facing challenges such as bottleneck issues due to business volume growth and system challenges. To address these challenges, we propose a design methodology for an IoT platform based on microservices. The platform's modules are divided into front end, database, security, and operation maintenance architecture, all effectively designed. Through practical applications, the platform enables interconnections between different information systems, production status monitoring, efficiency management, performance evaluation, energy consumption analysis, quality detection, and equipment asset evaluation. Finally, a data-driven deep learning algorithm, named Long Short-Term Memory Neural Network (LSTM) is developed for the state recognition of the industrial robot based on the Intelligent data services platform, which validate the effectiveness of the constructed IoT platforms. This platform offers advantages in extendibility, reusability, and provides methods for upgrading, expanding functions, and maintaining industrial IoT platforms in the discrete manufacturing industry.

INDEX TERMS Automobile manufacturing, IoT platform, microservices, deep learning, long short-term memory recurrent neural network (LSTM), state recognition.

I. INTRODUCTION

The expansion of businesses has led to the growth of system scales, presenting significant challenges in system extension and upgrades. To address these challenges, more enterprises are focusing on developing efficient and reliable Industrial Internet of Things (IIoT) platforms. These platforms aim to support ubiquitous network interconnection of devices, integrate heterogeneous data, unlock the value of data, accumulate industrial knowledge, and rapidly reuse applications. In 2023, China introduced the "Industrial Internet Platform Microservices Reference Framework," which sets standards for microservices within industrial internet platforms and offers guidance on developing capabilities for constructing such platforms based on microservices [1], [2]. Microservices can be independently deployed to implement specific functionalities for various applications. This architecture, widely used in sectors like hydropower [3], [4], [5], [6], smart cities [7], [8], [9], and rail transportation, Lin et al. [10], [11], offers excellent flexibility, scalability, and

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maintainability. In automotive manufacturing, key devices like industrial robots, spot welding machines, arc welding machines, and fans can be connected to the network. The state and attribute data from these devices can be integrated into the IIoT platform to obtain lifecycle data. Given the diverse data and knowledge types involved, the IIoT platform in automotive manufacturing requires high-performance functions [12], [13], [14]. The microservices architecture enables the partitioning of the entire system into independent services that can be efficiently orchestrated, deployed, executed, and maintained. This architecture enhances flexibility, reduces failure risks, and allows for scalability as needed [1], [15].

Despite its benefits, such as enhanced flexibility and scalability, there are several obstacles that organizations may encounter. With a large number of services that are dynamically scaled and deployed, managing service discovery and configuration settings becomes crucial. Maintaining an up-to-date registry of services and ensuring proper configuration management can be challenging. In a microservices architecture, each service may have its own database or data store. Ensuring data consistency and managing transactions across multiple services while maintaining data integrity can be challenging, particularly in distributed systems. In addition, implementing an Industrial Internet of Things (IIoT) platform for health condition monitoring in a manufacturing setting introduces specific challenges for evaluating performance. Monitoring the health and performance of manufacturing equipment and processes in real time using IIoT devices and sensors requires seamless integration with the microservices architecture.

To address the specific needs of the IIoT platform in automotive manufacturing, an architecture design and application of IIoT platform in automobile manufacturing based on microservices is proposed in this paper. This method enhances the maintainability and scalability of the IIoT platform in automotive manufacturing and is validated through practical engineering applications.

II. RELATED WORK

A. OVERIVEW OF PLATFORM

The IIoT platform is designed to cater to the requirements of digitization, networking, and intellectualization in the manufacturing industry. It offers a comprehensive service system that encompasses data integration, aggregation, and analysis. With its capacity to manage vast amounts of data, the IIoT platform enables seamless connectivity across diverse devices and provides elastic resources [16], [17]. Digital applications, industry expertise, and model knowledge are all centralized within the IIoT platform, making it the focal point for industrial resource allocation and driving the intelligent evolution of manufacturing systems [18], [19].

In the automotive manufacturing sector, companies are increasingly focusing on meeting their escalating demands for data analysis and strategic decision-making. This includes essential services like condition monitoring, fault diagnosis, and failure maintenance. As industrial big data, artificial intelligence, and cloud computing continue to advance, the operational scope of automotive manufacturers expands to cater to customer needs. Hence, establishing an IIoT platform in automotive manufacturing is crucial to enhance efficiency, conserve energy, and facilitate equipment maintenance for customers [20], [21].

B. THE DEFINITION AND ADVANTAGES OF MICROSERVICES ARCHITECTURE

Microservices is a cloud-native architectural approach that consists of small, loosely coupled, reusable components or services such as databases, data models, and business logic. These services are deployed independently and organized effectively based on the business logic [22], [23], [24]. This architecture is a modern evolution of traditional software application architecture, where system processes are broken down into granular services. Each service is an independent application that can provide APIs independently, leading to the development of what are known as "microservices". The overall architecture, encompassing development, testing, deployment, and more, is referred to as "microservices architecture". Adopting the microservices architecture can enhance developing efficiency and system stability [25], [26], [27]. In comparison to traditional monolithic applications, microservices offer several advantages:

(a) Simplified development and deployment. The granular services in the system exhibit characteristics of loose coupling, allowing individual microservices to be easily modified, iterated, and deployed quickly. This streamlined process makes debugging and maintenance tasks significantly easier.

(b) More flexible business expansion and contraction. Each microservice can be independently deployed, started, and stopped as the business grows and changes.

(c) Better fault tolerance and maintainability. Faults can be isolated effectively between microservices, and fault identification can be achieved quickly.

(d) Easy updates. Each microservice can be updated and iterated independently, making the system simple and highly maintainable.

(e) Improved team cooperation. Each microservice has its own business logic, focusing on a specific function, allowing developers to concentrate on resolving specific difficulties.

Furthermore, the adoption of deep learning techniques for intelligent maintenance enables the system to predict and prevent equipment failures, further enhancing the overall efficiency and reliability of the manufacturing process.

C. THE DECOMPOSITION OF MICROSERVICES

The platform in the automotive manufacturing industry, based on the requirements of digitization and single system decomposition technology [28], [29], [30], is divided into various microservices for efficient management:

a) Data Integration and Collection Microservices. As the foundation of the platform, these microservices are crucial for managing and utilizing multi-source information data.

b) Data Analysis and Modeling Microservices. These microservices are essential for preprocessing, analyzing, mining, and modeling integrated data, which enables informed decision-making.

c) Efficiency Management Microservices. Diagnosing production line issues and analyzing cycle time are critical for estimating the overall production line status and optimizing production efficiency.

d) Maintenance Management Microservices. Implementing intelligent maintenance management of production lines and spare parts services based on equipment life cycles and maintenance policies is vital for reducing downtime and increasing productivity.

e) Production Management Microservices. Monitoring real-time status of key equipment and tracing back variation characteristics are essential for ensuring production quality and reliability.

III. THE DESIGN OF PLATFORM ARCHITECTURE

The system architecture uses the way of layered designing, defines interfaces between different layers, establishes the loosely-coupled association. It enhances the reusability, scalability, and maintainability of modules. Simultaneously, it is conducive to divide into different modules and reasonably allocation the workload. The difficulty of integration id decreased by interface standard [31], [32], [33]. The layered framework of platform is illustrated in Figure 1, which consists of five parts: infrastructure layer, data Acquisition layer, data persistence layer, platform service layer, application layer, and support layer.

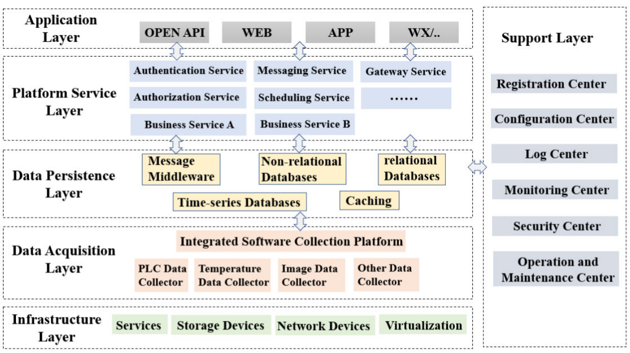

FIGURE 1. The layered framework of the platform.

Infrastructure Layer: It includes data center equipment room, server racks, servers, network communication equipment, and security protection devices, which ensures the safe and stable operation of the platform.

Data Acquisition Layer: It collects the multi-source information data based on intelligent sensors and collectors.

Data Persistence Layer: It provides the ability to store, access, and manage information, which involves relational database, time series database, memory database, and column-oriented database.

Platform Service Layer: It is the most important part of the platform, and encompasses the concrete implementation of all business functions.

Application Layer: It integrates different instances for external applications, including platform management, tenant management, interface management, and so on. It supplies the ability of second development.

Support Layer: It consists of registration center, configuration center, log center, monitoring center, security audit, and maintenance center.

A. OVERIVEW OF PLATFORM

As shown in Figure 2, the backend framework consists of three main components: a Kafka cluster, a database cluster, and a backend server cluster. The Kafka cluster acts as a data bus for integrating and caching data, while the database cluster stores raw data, processed data, and business data. The backend server cluster supports platform applications.

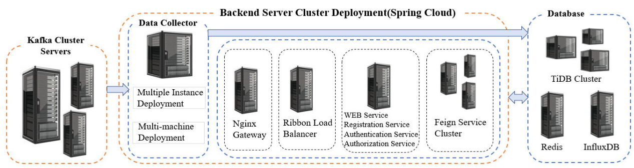

FIGURE 2. The framework of the backend.

In Figure 3, the SpringCloud framework comprises a server cluster, load balancer, gateway cluster, external services, service monitoring center, and authentication center. The server cluster deploys multiple microservices on the platform using container technology. Load balancing distributes requests across servers to improve data collection and analysis. The gateway cluster handles protocol transformation and ensures secure information exchange. The authentication center provides authentication and access control services. Additionally, the service monitoring center and registry center facilitate registration and subscription services.

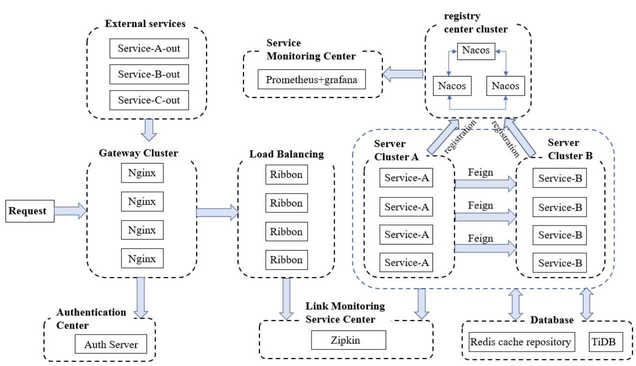

FIGURE 3. The SpringCloud framework.

B. THE DESIGN OF THE BACKEND ARCHITETURE

The framework of the frontend is shown in Figure 4, which includes gateway layer, data processing interaction layer, frontend UI layer, and access layer. The gateway layer is responsible for protocol conversion and information transmission between the frontend and the backend. The data processing and interaction layer utilizes the Vue components for data processing, and Axios is responsible for interacting with the backend. The frontend UI layer adopts Element-UI components to develop the H5 interfaces and Echarts to report interfaces. The access layer not only supports by web browsers such as Chrome but also supports by app and WeChat. The development tools such as Webpack are mainly used for project development, project packaging, and project building. The npm is used to install dependencies and publish applications. WebStorm is used for code debugging.

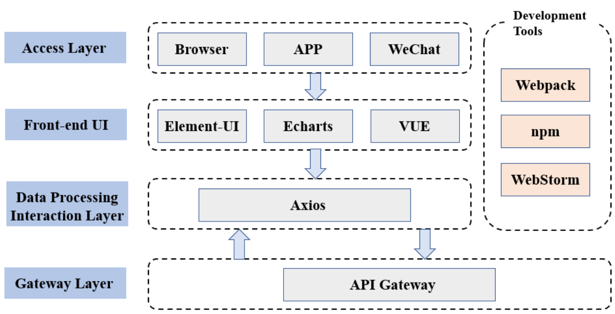

FIGURE 4. The framework of the Web frontend.

C. THE DESIGN OF THE DATABASE ARCHITETURE

The platform implements a modular database architecture design, deploying TiDB, Redis, and InfluxDB. TiDB utilizes a distributed storage architecture for long-term data storage, while Redis stores real-time calculation results and frequently accessed data. InfluxDB is utilized for storing time series data and operational monitoring data. The data sharing framework for multi-tenants is presented in Figure 5, where shared business microservices modules and various business domains are deployed to cater to the data needs of different tenants. This setup enables effective isolation of data and operations while achieving source sharing.

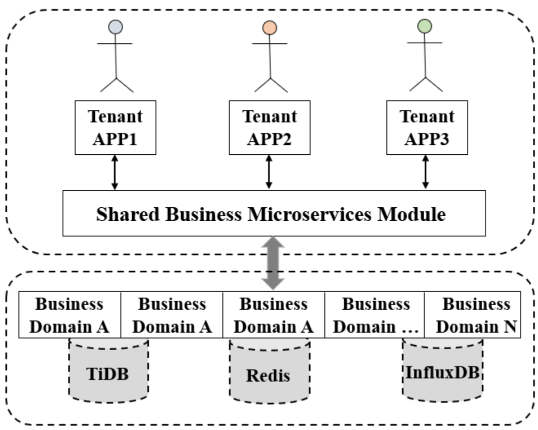

FIGURE 5. The framework of the data sharing for multi-tenant.

D. THE DESIGN OF THE SECURITY ARCHITETURE

The system adheres to three-level security protection requirements, addressing safety concerns in five key aspects: physical security, network security, application system security, host security, and data security.

Physical Security: Measures such as access control systems and video monitoring are implemented in equipment rooms to prevent unauthorized access.

Network Security: Firewalls, intrusion detection and prevention systems, and encryption protocols are utilized to strengthen internal and boundary protection.

Application Security: Multi-tenant application security is ensured by creating a private business information set for each new tenant and conducting code reviews.

Host Security: Vulnerability detection, virus intrusion detection, and malicious code detection are employed to enhance host security.

Data Security: Comprising data collection and upload, data processing and storage, and data visualization, as depicted in Figure 6. Registration authentication is used for data collection and upload, while data processing and storage utilize data backup, interface authentication, and identity authentication. Data visualization incorporates digital signatures and port control for added security.

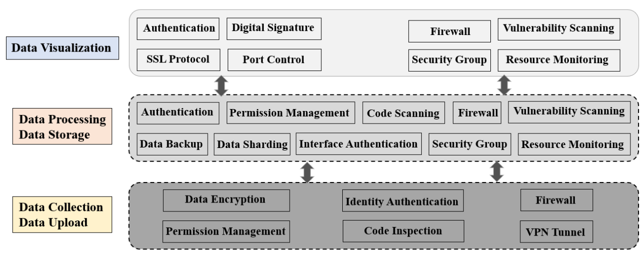

FIGURE 6. The framework of the data security for multi-tenant.

E. THE DESIGN OF THE OPERATIONS AND MAINTENANCE ARCHITETURE

As Illustrated in Figure 7, the operation and maintenance framework includes both online and offline maintenance services. Online maintenance services focus on monitoring the operational state and resource utilization of the platform, collecting fault messages, and optimizing resource allocation. Offline maintenance services are dedicated to analyzing log files. Maintenance issues are classified, addressed, and stored in a problem database. As information processing and data mining techniques advance, effective optimization solutions are developed.

IV. APPLICATION PRACTICE

A. INTELLIGENT DATA SERVICES PLATFORM

An intelligent data services platform has been established for an automobile manufacturing enterprise, with information barriers being broken down. Data collection, storage, processing, analysis, and mining are carried out on the platform.

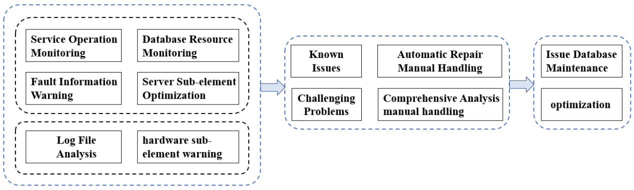

FIGURE 7. **The framework of the operations and maintenance.**

Data fusion and information exchange are achieved. The platform realizes six functional modules, such as efficiency management, energy consumption management, operation and maintenance management, production management, quality management, and asset management. The graphical interfaces of six functional modules are shown in Figure 8. The interface of the efficiency management is depicted in Figure 8(a). The Gantt chart is generated to assess the operation status from three dimensions: production line, equipment, and procedure. It considers the factor which affects the total effectiveness. Recommendations for performance optimization are provided.

In Figure 8(b), the interface of the energy consumption management is presented. Multidimensional reports of energy usage and consumption are generated automatically. The unreasonable link of energy-using is identified, and an energy-saving retrofit design is proposed. Figure 8(c) displays the interface of the operation and maintenance management. The entire lifecycle operational records of the equipment can be traced and analyzed. The failures of the equipment are predicted to increase the utilization rate of the equipment and balance the supply and demand of spare parts. The interface of the production management is illustrated in Figure 8(d). The real-time production status can be monitored. The real-time diagnosis of key equipment and processes is carried out. The interface of the quality management is shown in Figure 8(e).

B. STATE RECOGNITION OF THE INDUSTRIAL ROBOT BASED ON THE INTELLIGENT DATA SERVICES PLATFORM

The recognition of the state of industrial robots in the welding process of automobile manufacturing holds significant industrial value, directly impacting equipment stability, automobile quality, and energy consumption levels. Currently, motion state data of industrial robots can be acquired through the robot teach pendant or portable digital assistant (PDA). However, accurately recognizing the features and modes of motion states remains a challenge. To address this, a state recognition algorithm for industrial robots has been developed and implemented to evaluate real-time operational states. the algorithm follows a structured approach, as shown in Figure 9:

a) Data Collection and Preprocessing: Motion state data for each axis of the industrial robot is collected, stored, preprocessed, cleaned, and integrated using the intelligent data services platform. The speed of each axis is extracted for feature extraction and modeling.

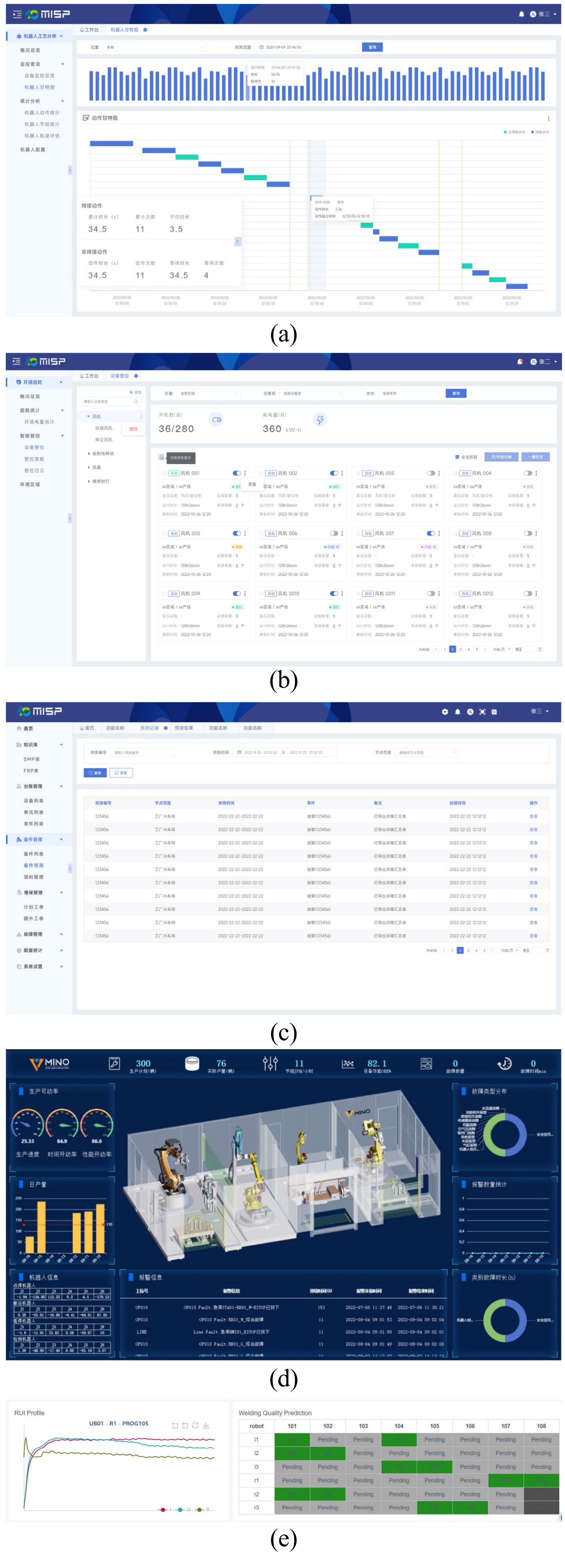

FIGURE 8. **The intelligent data services platform of an automobile manufacturing enterprise in Guangzhou, China. Figures 8(a)-(e) illustrate the interfaces of the efficiency management, the energy consumption management, the operation and maintenance, the production management, the quality management, respectively.**

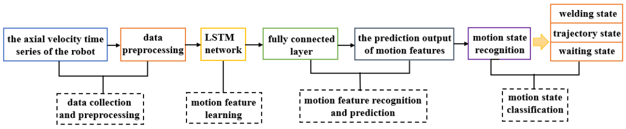

FIGURE 9. The framework for state recognition of industrial robot in welding process.

b) Motion State Data Classification: The preprocessed speed data is analyzed, labeled, and categorized into three states: welding state, waiting state, and trajectory state.

c) Motion Feature Learning: Deep learning techniques, such as convolutional neural networks have been widely used for intelligent maintenance [36], [37], [38], [39]. In this part, the preprocessed speed data is fed into a Long Short-Term Memory Recurrent Neural Network (LSTM), as shown in Figure 10 for feature exploration and learning. The LSTM model captures the relationships among data, updating internal states in each iteration to memorize relevant information and adjust states based on input. The model utilizes a three-layer LSTM network, each with 64 hidden units. The LSTM structure, depicted in Figure 10, incorporates an internal memory cell controlled by forget and input gate networks. The forget gate determines the retention of prior memory values, while the input gate regulates new input to memory cells. By adjusting gate states, LSTM can capture both long-term and short-term dependencies in sequential data. The LSTM formulation is defined as follows:

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

$$i_t = \sigma(W_i[h_{t-1} + b_i]) \tag{2}$$

$$o_t = \sigma(W_o[h_{t-1} + b_o]) \tag{3}$$

$$\tilde{c_t} = tanh(W_c[h_{t-1} + b_c]) \tag{4}$$

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c_t} \tag{5}$$

$$h_t = o_t \otimes tanh(c_t) \tag{6}$$

where f_t, i_t and o_t are forget, input and output gates respectively. They are component-wise multiplied by input, memory cell and hidden output to gradually open or close their connections. x_t is an input, h_{t-1} is an output layer at time $t-1$ and c_{t-1} is an internal cell state at $t-1$.

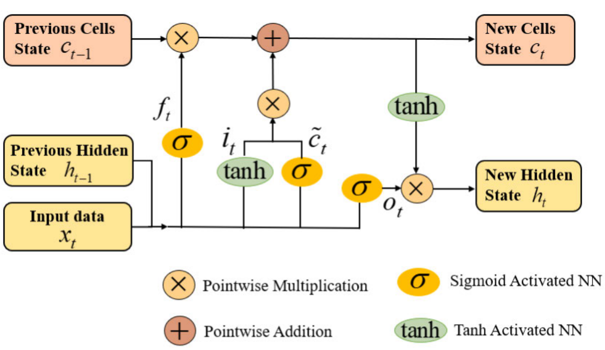

FIGURE 10. The gate mechanism diagram of LSTM.

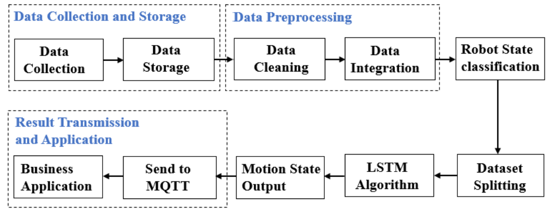

FIGURE 11. The diagram of data flow from data collection to platform application.

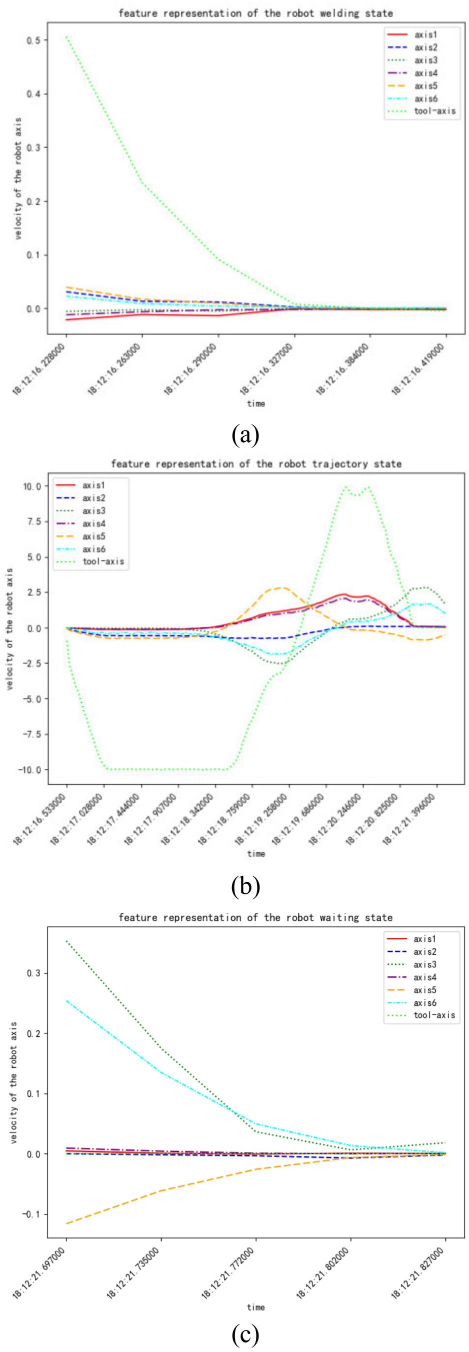

FIGURE 12. The feature diagrams of each state of the industrial robot.

d) State recognition and classification: The motion states are identified by training and testing the LSTM model. Once trained, the model is integrated into the platform to offer state recognition services for industrial robots. The entire process, starting from data collection to platform deployment, is illustrated in Figure 11.

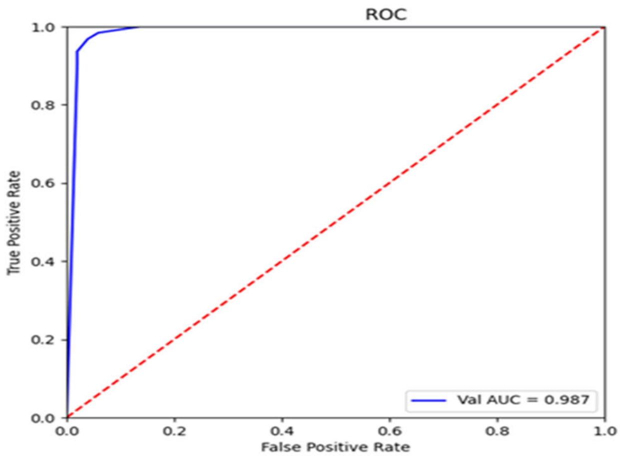

FIGURE 13. The ROC curve diagram of state recognition model.

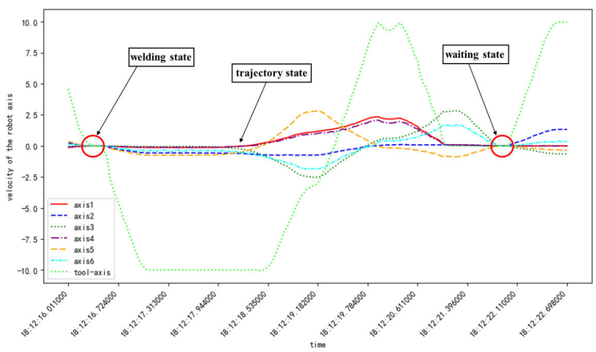

FIGURE 14. The results of state recognition of industrial robot in welding process.

The timing characteristics of welding state, trajectory state, and waiting state is presented in Figure 12. There is great diversity among the speed of each axis of the industrial robot, with the speed of the tool-axis changing mostly in trajectory and welding states. Conversely, the speed of axis 1 to 6 is nearly close to zero in welding state and exhibits a wide variation range in the trajectory state. The preprocessed speed data are used as the input of the LSTM model, and three motion states are chosen as the output. The state recognition model is trained and tested, and the final recognition results are shown in Figure 13.

In addition, the recognition results are evaluated using the ROC curve. ROC curve (Receiver Operating Characteristic curve) is a graphical representation of the performance of a binary classification model. It plots the true positive rate (sensitivity) against the false positive rate (1)-specificity) at various threshold settings. It helps to evaluate the trade-off between sensitivity and specificity of a model and determine the optimal threshold for making predictions. From the result, it can be seen that an AUC of 0.987 have been obtained, which present high recognition accuracy. The model is deployed in the run-time environment for continual evaluation.

The findings from Figure 14 highlight the successful application of the LSTM model in recognizing the motion state of industrial robots during welding processes. This not only validates the effectiveness of utilizing advanced machine learning techniques in industrial settings but also opens up opportunities for further enhancements in efficiency and accuracy. Continued research and development in this field could lead to the optimization of industrial robot operations, ultimately improving productivity and quality in manufacturing processes.

V. CONCLUSION

Based on functional and technical requirements, the architecture of IIoT platform in automobile manufacturing based on microservices is designed which consists of five parts: the backend architecture, the frontend architecture, the database architecture, the security architecture and the Operations and Maintenance Architecture. The proposed method is proved through the practical applications. The developed platform could realize the interconnections between different information systems, monitor the production status, promote production efficiency, evaluate the application effects of the equipment, analyze the status of energy consumption, detect the product quality, guarantee the machining precision and provide the effective and reasonable assessment of the customer assets. The digital and intelligent level of automobile manufacturing enterprises can be improved. Further research is prospected that the security and the reliability of the system should be enhanced through the information security technologies, industrial big data technologies, and artificial intelligence technologies.

Moving forward, future work should focus on enhancing the security and reliability of the IIoT platform in automobile manufacturing through the integration of advanced information security technologies, industrial big data technologies, and artificial intelligence. By implementing robust security measures and leveraging cutting-edge technologies, the platform can ensure data integrity, confidentiality, and availability while proactively identifying and mitigating potential threats.

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Author Contributions: The authors join in data collection, analysis, and interpretation of results, draft manuscript preparation; Zhuyun Chen: supervision and revise the manuscript. They reviewed the results and approved the final version of the manuscript.

Availability of Data and Materials: The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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