Network Distribution for Damage Warning System with Cloud-Edge Collaborative Architecture

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***Abstract*—This paper designs a distribution network external force damage early warning system based on audio classification technology, focusing on the potential damage that large construction machinery might cause to cables. By utilizing audio data, the system can accurately monitor and analyze the real-time status of construction sites to identify potential cable damage activities. Leveraging a cloud-edge collaboration architecture, the system employs cloud-based model training and edge computing technology to achieve real-time monitoring and data processing, thereby enhancing the accuracy and timeliness of warnings. Integrating machine learning algorithms and pattern recognition technology, the system can automatically analyze and predict the impact of construction machinery on cables. Through a visualization system, it provides real-time warnings and response measures, effectively reducing losses caused by external damage and ensuring the safe operation and reliability of the distribution network and power supply*.

Keywords—Distribution Network, External Force Damage, Early Warning System, Cloud-Edge Collaboration

I. INTRODUCTION

With the acceleration of urbanization and the advancement of industrialization, large construction machinery plays an increasingly important role in urban construction and infrastructure maintenance. However, during operation, these machines may unintentionally cause external damage to surrounding power distribution equipment, especially cables. Such damage can lead to power supply interruptions and equipment failures, adversely affecting urban life and economic activities.

Traditional monitoring and early warning methods for power grid operation and maintenance include sensor monitoring and manual inspections. However, these methods often face limited monitoring range, insufficient real-time capabilities, and low data processing efficiency. Literature [1] introduced the Smart Grid (SG) concept, envisioning the construction of a self-healing, reliable power grid protection system to prevent malicious damage and natural disasters. With the development of the Internet of Things (IoT), cloud computing, and artificial intelligence (AI) technologies, AI-based power grid systems are gradually becoming a new direction for addressing these challenges. Applying IoT technology to smart grids is an important approach to accelerating the construction of online monitoring systems for transmission lines. Advanced IoT sensing and communication technologies can effectively prevent or mitigate natural disaster impacts on transmission lines [2]. Additionally, AI-assisted analysis improves fault detection, enhancing the system's "intelligence" [3, 4]. To further improve communication efficiency and early warning timeliness, solutions combining cloud-edge collaboration and AI are also emerging in smart grid scenarios [5].

Specifically, the frequent threat to transmission lines posed by construction activities has led to the development of many AI-based solutions targeting external force damage to distribution networks. Literature [6] proposed a deep learning-based external force damage detection method for transmission lines using object detection technology, effectively identifying construction machinery in surveillance footage. Building on object detection, literature [7] integrated a backend inference module and proposed an external force damage detection algorithm for distribution networks based on deformable convolutional networks [8]. This approach improves the detection capability of deformable convolutional networks for external force damage by analyzing the positional relationship between detected construction vehicles and their background. However, object detection also has limitations in the context of early warning for external damage, such as blind spots in monitoring coverage and the difficulty of collecting large amounts of image data. Therefore, this paper introduces the ECAPA-TDNN voiceprint recognition model proposed in the literature [9] and develops a system that uses the audio classification for early warning of external damage during construction.

This paper aims to develop a cloud-edge collaborative architecture-based early warning system for external force damage to distribution networks. Utilizing deep learning technology based on audio classification, the system achieves real-time monitoring and early warning of potential cable damage caused by large construction machinery, thereby enhancing the distribution network's safety management capabilities and ensuring the reliability and stability of transmission lines.

II. Design of the Distribution Network External Force Damage Early Warning System

A. System Architecture

This section describes the overall structure of the Distribution Network External Force Damage Early Warning System and the functions and interactions of its various components. As shown in Figure 1, the system mainly comprises the data acquisition layer, edge computing layer, cloud computing layer, and user interaction layer.

1. Data Acquisition Layer. a. Audio Sensors: Deployed around construction sites, these sensors collect real-time audio data to monitor activities of construction machinery that might cause damage to cables.

2. Edge Computing Layer. a. Edge Nodes: These are computational devices deployed on-site that can process and analyze audio data initially. The edge nodes run audio classification models for real-time analysis and preliminary warnings, reducing data transmission latency. b. Data Preprocessing: At the edge nodes, audio data undergoes preprocessing, including noise reduction, feature extraction, and initial classification. c. 4G Transmission: Using 4G networks, the preprocessed data and preliminary warning results are transmitted to the cloud, ensuring timely and reliable data transmission.

3. Cloud Computing Layer. Data Storage: The cloud stores many historical audio data and related analysis results, supporting model training and optimization.

4. User Interaction Layer. a. Frontend Display: Based on the Vue 2 and OpenLayers frameworks, this layer provides a dynamic, responsive user interface, offering real-time warning information and visualization of construction sites. b. Management Backend: Built on the Spring Boot framework, this backend offers system configuration and management functions, including configuring the location information of warning devices and managing and displaying construction announcements. c. Real-Time Alerts: Through a frontend visualization dashboard and mobile applications, real-time external force damage warnings are provided to users, helping them take timely countermeasures.

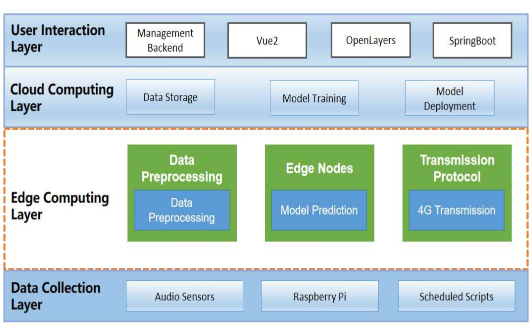

Fig. 1. System Framework Diagram

B. Hardware

The system's hardware is centered around a Raspberry Pi and integrates a quickly installable early warning structure. The setup is illustrated in Figure 2.

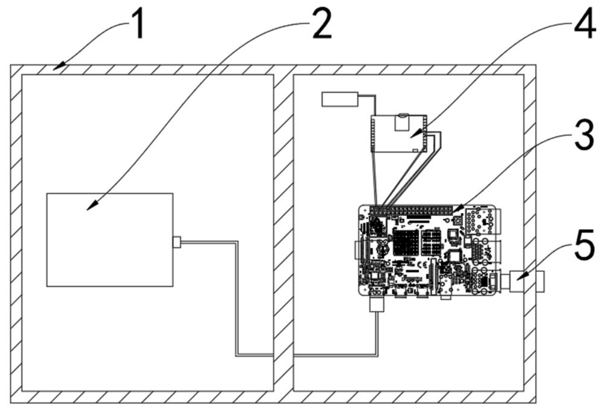

Fig. 2. Internal Structure Diagram of the Hardware Enclosure

1. Enclosure, 2. Power Supply Module, 3. Raspberry Pi Board, 4. Communication Module, 5. Microphone

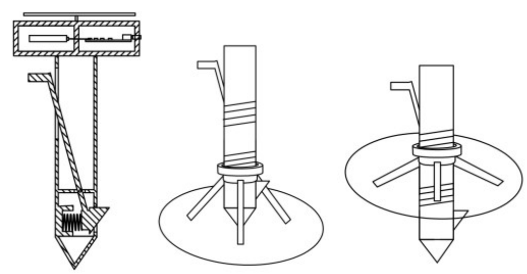

Fig. 3. Hardware Enclosure Support Structure Diagram

The early warning device features an enclosure (1) that houses a power supply module (2). The output of the power supply module (2) is connected to the Raspberry Pi board (3), while the output of the Raspberry Pi board (3) is connected to the communication module (4). A microphone (5) is securely mounted on the enclosure (1), and its output is connected to the Raspberry Pi board (3). The bottom of the enclosure (1) is equipped with removable support rods, and as shown in Figure 3, these rods have a height-adjustable triangular support structure. A solar panel is fixed on the top of the enclosure (1) and connected to the power supply module (2) to charge the module using solar energy.

Specifically, the audio warning model is deployed on the Raspberry Pi (3), and the microphone (5) is connected to the Raspberry Pi board (3) via a USB interface. The power supply module (2) provides 5V power through a Type-C interface connected to the Raspberry Pi board (3). The communication module (4) is a 4G communication module connected to the RXD and TXD pins on the Raspberry Pi board (3) via TXD and RXD lines. This module transmits warning results to the server. By using the 4G module for transmission, the device overcomes the limitations of WiFi and significantly enhances its environmental compatibility.

During operation, the microphone (5) collects audio data from around the power distribution equipment and transmits it to the Raspberry Pi board (3). The Raspberry Pi board (3) processes and analyzes the audio data using the deployed model to predict potential threats. If construction machinery that might damage cables is detected, the communication module (4) sends the warning results to the server.

C. *AUDIO FEATURE EXTRACTION MODEL*

Dataset Creation

A script was used to scrape construction site videos from the internet, followed by audio extraction and segmentation from these videos. The extracted audio data underwent preprocessing, including pre-filtering and wavelet denoising, and was labeled accordingly to create an initial dataset.

After segmenting the audio, the preliminary dataset contained just over 4,000 entries. Data augmentation was performed using time interval shifting to address the small sample size, increasing the number of data entries to over 8,000. To further expand the dataset, adversarial audio was generated using the HIFI-GAN model, bringing the total number of entries to 10,000.

Model Training

The ECAPA-TDNN model was used to train the custom audio dataset. The ECAPA-TDNN model, introduced by Desplanques et al. from Ghent University in 2020, consists of an initial frame layer, three SE-Res2Blocks modules, an attention-based statistical pooling layer, and three fully connected (FC) layers. This model offers several advantages over traditional audio classification approaches: 1. Channel Attention: The frame and statistical pooling layers incorporate SE modules that explicitly model inter-channel dependencies and recalibrate channels based on global properties. This design allows the network to capture important information better and enhance the quality of audio embeddings. 2. Propagation and Aggregation: By introducing skip connections, the system propagates and aggregates channel features, leveraging hierarchical features learned at different layers and combining them to improve overall representation. 3. Multi-Scale Res2Net Features: The initial frame layer is restructured into a one-dimensional Res2Net module, which captures multi-scale features through effective skip connections and dilated one-dimensional convolutions. This design reduces model parameters while improving system performance. 4. Attention-Based Statistical Pooling Layer: Incorporating attention mechanisms and global context information enhances the performance and robustness of the pooling layer.

The training was conducted on the following hardware configuration: Intel Core i9-12900KF CPU, NVIDIA RTX 3080Ti GPU, and 64 GB RAM. The model was trained for 90 epochs with a batch size of 64. The accuracy and loss trends on the test set are shown in Figure 4. The model's performance stabilized after 90 epochs, indicating that accuracy has converged. The final classification accuracy achieved was 94.365%. This demonstrates that the model performs well for the classification task.

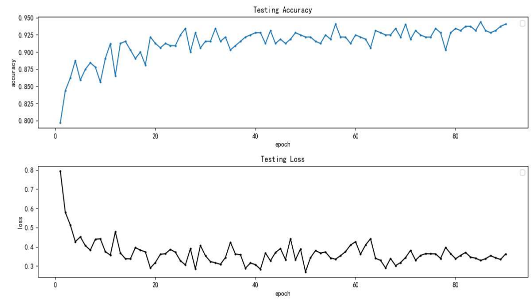

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Fig. 4. Training Results Trend of the ECAPA-TDNN Model

D. Integration of the Early Warning System in Cloud-Edge Collaborative Architecture

Cloud-Edge Collaborative Architecture

The cloud-edge collaborative architecture is a system framework that combines cloud computing and edge computing to leverage the strengths of both cloud and edge nodes for efficient data processing and intelligent analysis. In this architecture, the warning system uses edge nodes (hardware designed around Raspberry Pi) for on-site data collection, preliminary processing, and prediction. At the same time, the cloud utilizes its powerful computing capabilities and extensive data resources for model training and optimization. The trained models are then deployed back to the edge nodes. This cloud-edge collaborative approach enables real-time responses, reduces cloud load, enhances data processing efficiency, and ensures continuous model optimization, thereby significantly improving the overall performance and reliability of the system.

Prototype Implementation

The backend of this system is supported by the Spring Boot framework, which integrates with the Vue 2 frontend and OpenLayers to provide a visual display of real-time external force damage warnings. The backend, built with Spring Boot, handles data processing, business logic, and interface management, receiving warning information from edge nodes and storing and transmitting these warnings to the front end. The front end utilizes Vue 2 to create a dynamic and responsive user interface. OpenLayers is the map engine, offering robust geographic information processing and map rendering capabilities to visually present warning information on a large display screen. Users can monitor the site in real-time through this visual display and make prompt decisions. This design not only enhances data readability and response speed but also significantly improves the safety monitoring capabilities of the distribution network.

The warning device configuration is managed through the backend, ensuring accurate management and monitoring of each device's geographic information. Additionally, the system provides construction announcement management and display features. Users can publish and manage construction announcements via the backend, which are then displayed in real-time on the front end. This supplementary information helps users comprehensively understand the construction site conditions, thereby improving the accuracy and response speed of the warnings.

System Display

As illustrated in Figure 5, the visual display screen is divided into three sections: left, center, and right. The upper part of the left section shows a historical warning frequency leaderboard, assisting users in diagnosing areas with high external damage risks. The lower part of the left section displays historical warning information; users can click on an item to have the map jump to the event location and display detailed information. The central section features the map, allowing users to understand warning locations and related information visually and in real-time. The right section lists construction announcements, providing users an easy way to view and manage these notices.

As shown in Figure 6, the management backend consists of three major functional modules: warning hardware management, warning information management, and announcement management. The warning hardware management module configures and maintains the location and status of warning devices. The warning information management module handles and stores warning event data. The announcement management module is used to publish and manage construction announcements, ensuring that these notices are promptly displayed on the front end.

Fig. 5. Frontend Visualization Display Screen

Fig. 6. Management Backend

III. Summary

This paper designs a distribution network external force damage warning system based on audio classification technology, focusing on detecting and warning about potential damage to cables caused by large construction machinery. Compared to traditional manual fault location inspection, this method improves risk warning capabilities and saves significant human and material resources by classifying events as external force damage. The system utilizes a cloud-edge collaborative architecture for real-time monitoring and data processing, integrating machine learning algorithms and pattern recognition technology to enhance the accuracy and timeliness of warnings. Experimental results demonstrate that the system effectively identifies and predicts the impact of construction machinery on cables, providing timely warnings and response measures, thus reducing losses from external damage and ensuring the safe operation of the distribution network and reliability of power supply.

In the future, we will continue to optimize the cloud-based model further to enhance the performance and adaptability of the warning system. We also plan to explore additional application scenarios, such as integrating official construction announcement information using web scraping technology, mapping it onto OpenLayers, and providing real-time supplementary warnings. These efforts aim to improve the intelligent management level of the distribution network comprehensively.

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