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A CNN Based Anomaly Detection Network for Utility Tunnel Fire Protection

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Abstract: Fire accident is one of the significant threats to the urban utility tunnel (UUT) during operation, and the emergency response is challenging due to the compact tunnel structure and potential hazard sources involved. Traditional fire detection techniques are reviewed in this study, and it has been determined that their performance cannot satisfy the requirements for early fire incident detection. Integrating advanced sensing technologies and data-driven anomaly detection has recently been regarded as a feasible solution for intelligent safety system implementation. This article proposed an approach that utilized a fiber-optic distributed temperature sensing (FO-DTS) system and deep anomaly detection models to monitor the fire exotherm during the early stages of accidents. The variable fire exotherm is simulated with an embedded-system controlled electrical heating platform. Moreover, autoencoder (AE) based and convolutional neural network (CNN) based methods have been designed for anomaly detection. The temperature data collected from the FO-DTS in the experiment was employed as the training set for the data-driven models. Furthermore, the anomaly detection models were tested, and the results showed that the proposed CNN model can achieve a higher accuracy rate in detecting the simulated fire exotherm.

Keywords: intelligent fire detection; anomaly detection; CNN; urban utility tunnel

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1. Introduction

The urban utility tunnel (UUT) is a critical facility of the urban infrastructure which carries several lifelines, such as the gas pipeline, water supply, sewer system, and electrical and communication cables for modern cities. The encouragement of underground UUT is an environmentally friendly development option, which avoids occupying limited land resources during urbanization. However, some UUT corridors are generally identified as high-risk sources, since they contain gas and high-voltage electrical pipelines. According to the previous studies on temperature distribution, exotherm release rate, and smoke propagation, the fire behavior in UUT is rapid, violent, and difficult to control due to its compact structure and complex environment [1,2]. Moreover, fire incidents are challenging to the emergency response system and likely cause coupling and secondary disasters [3,4]. Therefore, the deployment of reliable fire detection systems is significant during UUT operation and maintenance.

Flame fire detectors, fiber Bragg grating (FBG) detectors, video cameras, thermal cameras, and fiber-optic distributed sensing systems (FO-DTS) are the most common UUT fire detection solutions [5–7]. Wang et al. [8] proposed a densely spaced FBG array for small fire recognition and location. The FBG sensors were applied to prevent fire disasters by monitoring the power cable joint temperature in underground UUT [9]. A computer vision based method is presented to capture the features of camera images for fire and flame detection [10]. Han and Lee [11] designed a robust image processing algorithm for automatic real-time flame and smoke detection in tunnels. The performance of FO-DTS in underground mine environment monitoring is studied for safety control purpose [12].

Saxena et al. [13] developed a Raman optical fiber distributed temperature sensor system to monitor the progress of unforeseen fire events of a power supply cable in the tunnel. Besides the above techniques, there are studies employing hybrid methods for detecting fire incidents. Murillo et al. [14] demonstrated a system that combines infrared and visual image processing for fire detection in open areas. Sharma et al. [15] presented an integrated fire detection system using wireless sensor networks, UAVs, and cloud computing for smart cities.

For sensor data analysis in fire detection, machine learning has been accepted as the mainstream method in past decades. Fang et al. [16] presented a machine learning model to identify residential room fire development stages with fireground temperatures. A Faster R-CNN vision-based network was integrated with the indoor fire safety system to detect fire accidents in buildings [17]. Wu et al. [18] designed a CNN object detection model to prevent potential fire accidents in petroleum and chemical factories. A detection transformer based object detection model is constructed for fire and smoke detection [19]. Currently, machine learning implementations in fire detection mainly focus on image processing [20]. Meanwhile, several studies also consider data-driven models with other types of sensor data for fire detection. For instance, Martinsson et al. [21] proposed a machine learning approach to detect fire incidents in a laboratory scale test with acoustic sensor signals. Gao et al. [22] introduced a YOLOv5 based computer vision model to recognize coal fires with ground-penetrating radar. Wu et al. [23] established an LSTM model to predict the fire source information in a small-scale tunnel with the training data gathered from a numerical database.

Integrating emerging sensing technologies and data-driven algorithms is significant for constructing reliable and intelligent fire detection systems. As an intrinsically safe sensing technology, FO-DTS measures up to tens of kilometers through the reasonable arrangement of the optical fibers and collects dense spatial temperature distribution data to support the anomaly detection model development. The FO-DTS is considered as a proper instrument for fire detection in UUT, based on these metrics. However, the current FO-DTS fire detection systems mainly rely on a preset temperature threshold or rise rate criteria, which need to be improved to support accurate detection and decision making for emergency response. Therefore, this study proposed a CNN based deep anomaly detection network to process the sensing data and enhance the performance in monitoring the anomaly temperature variance caused by exothermic reactions in the early stages of UUT fire incidents.

The structure of this paper begins with describing the methodology, architecture, and main components of the proposed anomaly detection system in Section 2. Section 3 introduces the experimental setup and the test scheme used to evaluate the performance of the system. Section 4 provides detailed experimental results and discussions. Finally, the conclusions and suggestions for future work are given in the last section.

2. Methodology

2.1. System Architecture

A system is proposed to monitor the anomaly temperature variance in high-risk utility corridors to prevent potential fire accidents. The FO-DTS, sensing data collection, and deep anomaly detection models are the main components of the system, as demonstrated in Figure 1. The sensing optical fibers are installed in corridors with hazard sources to monitor the abnormal changes in ambient temperature. The sensing data will be converted and transmitted to the database server through the gateway. The deep learning models continuously fetch data from the database and check if the returned signals represent an anomaly.

2.2. Fiber-Optic Distributed Temperature Sensing

The optical time domain reflectometry (OTDR) and the Raman scattering effect are the theoretical foundation for developing an optical fiber distributed sensing system [24,25].

The temperature distribution along an optical fiber can be detected by measuring the Raman backscattering of the stokes and anti-stokes lights [26].

$$\frac{1}{T} = \frac{1}{T_0} - \frac{k_B}{k_B \Delta_\nu} \ln \frac{\Phi_{AS}(T)\Phi_S(T)}{\Phi_{AS}(T_0)\Phi_S(T_0)} \tag{1}$$

where T_0 is the reference temperature, k_B is Boltzmann constant, the phonon frequency $\Delta_\nu = 1.32 \times 10^{13}$ Hz, and Φ_S, Φ_{AS} is the luminous power of the Raman backscattering of the stokes and anti-stokes lights, respectively.

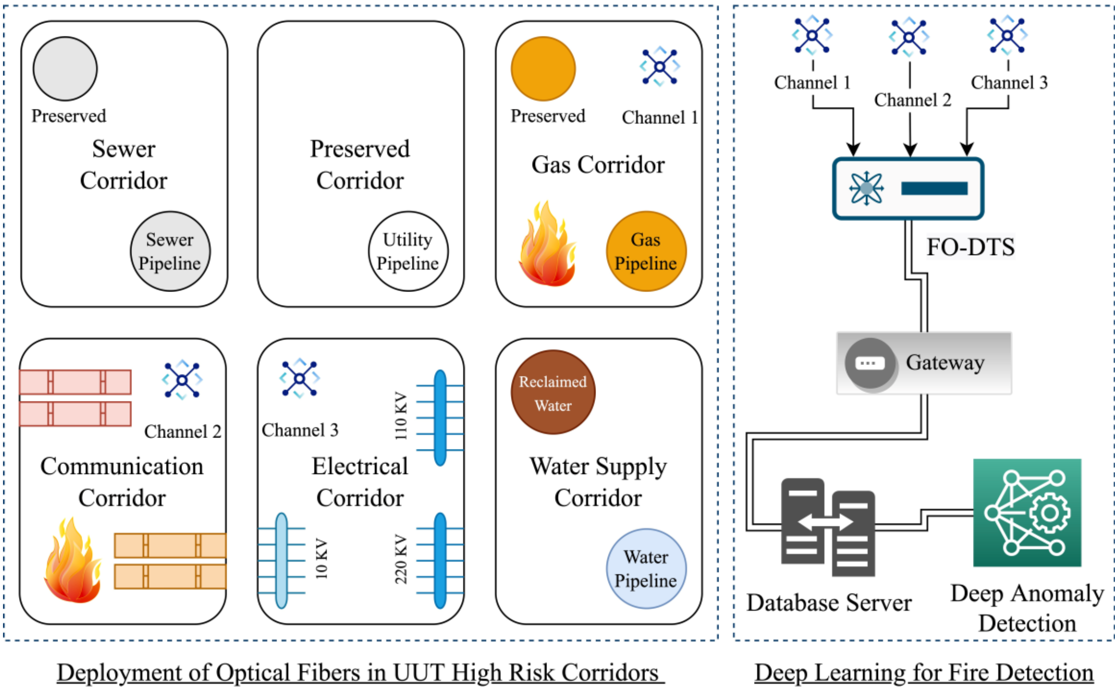

Figure 1. The architecture of the proposed intelligent fire detection system.

The temperature distribution at each point in the space where the optical fibers are located modulates the intensity of the Raman backscattering in the fiber, and the Raman backscattering signal with sensed temperature is collected through a wavelength division multiplexer and a photodetector. After demodulation, the temperature is extracted from the noise in real-time. In the time domain, according to the propagation speed of the light wave in the optical fiber and the interval of the backlight returning to the initial laser emitter, the OTDR based approach is used to locate the returned temperature point in the optical fiber.

2.3. Protocol Conversion and Data Storage

Traditional fire detection systems generally provide the function of alarm and linkage triggering, according to the preset threshold. In most cases, the daily monitoring data under normal conditions will not be recorded, since they are considered as a burden on the database server. However, for data-driven anomaly detection methods, a tremendous amount of sensing data containing normal and abnormal status information is the basis for establishing robust and reliable detection models. Therefore, a protocol conversion program is designed to collect field data returned from FO-DTS and forward them to a MySQL database. The flowchart of the protocol conversion and data storage program is shown in Figure 2. Through this process, the system will have the ability to store a sufficient amount of data from the fire detection system, and the proposed deep learning models can learn the characteristics of various states from the dataset.

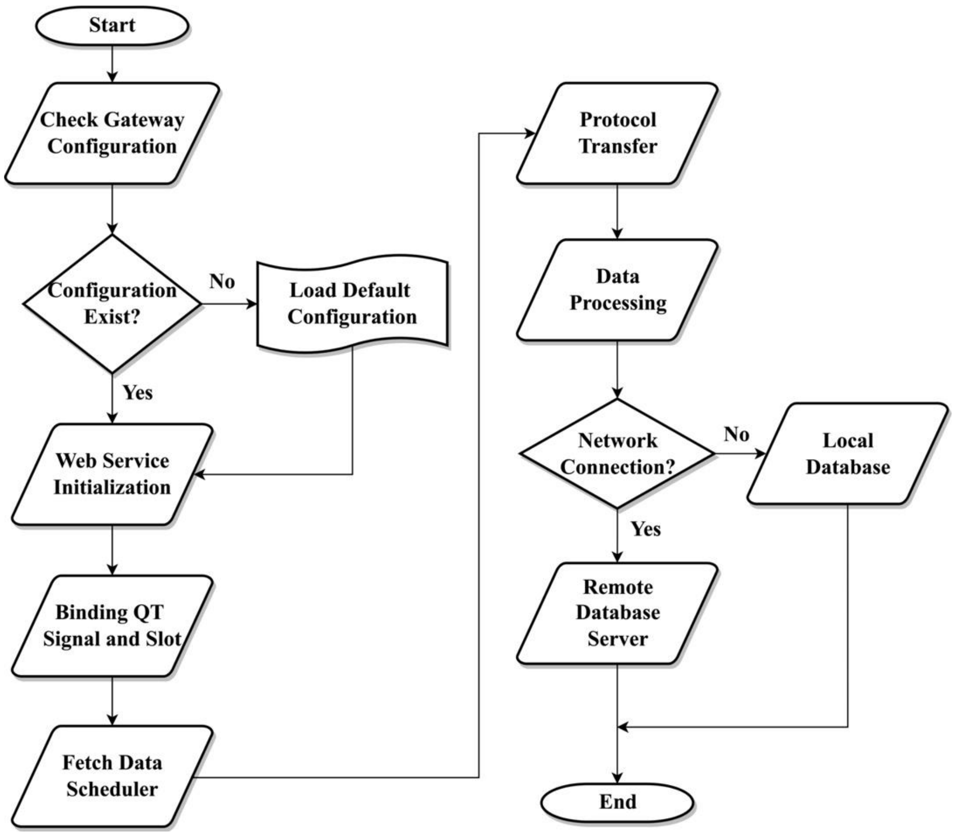

Figure 2. The flowchart of the protocol conversion and data storage program.

For infrastructure such as UUTs, fire detection and localization are both essential functions that must be available in the safety system, and the continuous temperature data collected by the FO-DTS needs to be mapped to real locations for emergency response, especially for high-risk areas. A location marker algorithm is designed to correlate the sensing data with the spatial position, and it will run when installing the optical fibers. The program is carried out as follows:

(1) Fully touch the optical fibers placed at the locations that need to be mapped with sensing data to a heating source (10 °C above the highest ambient temperature) and hold for 30 s.
(2) Start the location marker program to fetch data from the FO-DTS and obtain unprocessed continuous temperature data frames.
(3) Search for the data point with the maximum temperature value and identify its corresponding data sequence number; associate this sequence number with the actual spatial location in the program. Complete the location marker process for all critical points of the deployed UUT optical fibers.
(4) The data processing module in the gateway will reorganize the measurement data according to the association rules generated previously.

Therefore, the sensing data stored in the database will possess the actual position markers to map each focus area's starting and ending positions. The fire detection system can accurately predict and locate hazards after detecting fire incidents.

2.4. Deep Anomaly Detection Models

The combustion reaction exotherm in fire incidents will cause abnormal changes in the ambient temperature. Therefore, UUT fire detection can be carried out by identifying irregular temperature data returned by DTS. The rules-based, statistical, or traditional machine-learning anomaly detection models are currently prevailing in anomaly detection applications [27,28]. A specific preset alarm temperature or temperature rise rate is commonly used to determine whether collected sensor data is anomalous for fire detection systems. However, the ambient temperature is dynamic and could be affected by certain regular and random factors in UUT. It is challenging for the current anomaly detection models to accurately distinguish the irregular temperature variance from normal data. Therefore, two deep anomaly detection models based on neural networks are presented in this study to perform automatic feature generation and detection.

2.4.1. Autoencoder Based Anomaly Detection Model

A typical autoencoder (AE) learns the input dataset's features and reconstructs them sequentially through an input layer, a hidden layer, and an output layer. An autoencoder's structure can be divided into two parts: encoder $f_{\varnothing}$ and decoder g_{θ} [29]. For dataset $x^{(i)} \in \mathcal{R}^D$ $(1 \le i \le N)$, the encoder $f_{\varnothing}$ will map the input vector $x^{(i)}$ to a latent representation $h^{(i)} \in \mathcal{R}^M$ $(1 \le i \le N)$, and the AE decoder g_{θ} maps the $h^{(i)}$ back to the original input space as reconstruction $\hat{x}^{(i)} \in \mathcal{R}^D$ $(1 \le i \le N)$. The code space $\mathcal{R}^M$ usually has fewer dimensions than the message space $\mathcal{R}^D$. The learning objective of the AE network is to minimize the reconstruction error $\mathcal{L}$ between $x^{(i)}$ and $\hat{x}^{(i)}$.

$$\mathcal{L} = \sum_{i=1}^{N} \left\| x^{(i)} - g_{\theta}(f_{\varnothing}(x^{(i)})) \right\|^2 \tag{2}$$

Table 1 illustrates the details of the constructed autoencoder. The AE model is trained on the normal dataset, and the reconstruction errors during the training process will construct the error set E. Meanwhile, the anomaly detection parameter q is artificially determined according to the distribution of the training reconstruction errors to computer e_q, the q-th percentile of E. The loss between the original input and the reconstructed data of the anomalies will be greater than the normal losses. The AE based anomaly detection model takes the test dataset as the input and generates the reconstruction error e_i of each input t_i. If $e_i > e_q$, t_i is classified as an anomaly; otherwise, it is normal.

Table 1. The brief structure of the constructed AE network.

Type	Layer	Description
Encoder (Sequential)	(0) Linear (1) ReLU (2) Linear (3) Sigmoid	in-features=10, out-features=16 activation function in-features=16, out-features=12 activation function
Decoder (Sequential)	(0) Linear (1) ReLU (2) Linear (3) Sigmoid	in-features=12, out-features=16 activation function in-features=16, out-features=10 activation function

2.4.2. CNN Based Anomaly Detection Model

Convolutional neural networks (CNN) have shown excellent performance in computer vision, and CNNs can also be used to process time series signals. The convolution kernels applied to the images are two-dimensional, while the convolution kernels applied to the time series are one-dimensional. The convolution of the signal sequence x and convolution kernels w is defined as:

$$y = w * x \tag{3}$$

where $*$ is the convolution operation.

CNNs are typically constructed of convolutional layers, pooling layers, and fully connected layers. The convolutional layer extracts the local features of an input signal and generate the feature maps. In order to improve the representation ability of convolution, multiple feature maps can be generated in each layer to represent the characteristics of the input, which is controlled by the number of convolution kernels. The pooling layer is used to perform the feature selection and dimension reduction of the generated features. Therefore, the network parameters can be reduced in the training process. The fully connected layer is located at the end of the CNN, integrating the features extracted from the previous layers and mapping these features to the label space. Finally, the results will be input to the activation function, completing the classification.

In this paper, an anomaly detection model based on one-dimensional CNN is designed, which can automatically learn time series data features and classify them. The batch normalization layers are also employed to make the learning process more stable and avoid overfitting [30]. The structure of the proposed CNN anomaly detection network is demonstrated in Table 2.

Table 2. The brief structure of the one-dimensional convolutional neural network.

Type	Layer	Description
Sequential	(0) Linear	Conv1d (1, 16, kernel_size=(2,), stride=(1,), padding=(1,))
	(1) ReLU	activation function
	(2) Batch_Norm	BatchNorm1d
	(3) Linear	Conv1d (16, 8, kernel_size=(2,), stride=(1,), padding=(1,))
	(4) ReLU	activation function
	(5) Batch_Norm	BatchNorm1d
	(6) MaxPooling	MaxPool1d (kernel_size=3, stride=3, padding=0, dilation=1)
	(7) Linear	in-features=32, out-features=10
	(8) ReLU	activation function
	(9) Linear	in-features=10, out-features=1
	(10) Sigmoid	activation function

3. Experiment

3.1. The Experimental Setup

Fire detection is essentially achieved through accurate and sensitive monitoring of the irregular heat released into the environment at various rates. The experiment is designed to generate a set of temperature data collected at different heat release rates for data-driven anomaly detection model development and verification. However, due to the diversity of the causes of fire, the properties of combustibles, and combustion conditions, it is unlikely to collect sufficient abnormal data samples through actual combustion experiments. For instance, the burning heat caused by electrical failures is released at a relatively slow rate, while gas leakage induced accidents will be fiercer. Therefore, the electric heating simulation platform is designed to provide various heat release rates to generate a valid abnormal dataset. The combination of the heat release rates can approximately indicate the fire intensity in the early stages of the accidents.

This research mainly focuses on the identification of the abnormal temperature variation using the data collected by the FO-DTS and the proposed deep anomaly detection models. In practice, the FO-DTS can realize continuous long-distance temperature measurement and obtain a large amount of dense spatial sensing data, while these data are currently underutilized. The small-scale experiment can be employed to fundamentally study the basic laws of this method, which is always a feasible approach for expensive and destructive fire research. The presented experiment is the basis for future research on long-distance detection, and it can provide qualified training data for the data-driven anomaly detection models for this study.

In the experimental setup depicted in Figure 3, a customized heating module (100 mm $\times$ 100 mm) is installed on the back of the test iron plate. Five electrical heating rods (120 W) are embedded in the heating module, and a solid-state relay drive controls the heating power with the pulse width modulation generated from an embedded system. Three sensing optical fibers are attached parallelly onto the front surface of the iron plate (A1, A2, A3) for temperature measurement. The mounted length of each optical fiber is 500 mm, and the adjacent optical fibers are 15 mm apart. In the test plate, the temperature in the central position of the heating module is basically the peak of the temperature distribution, for there will be less heat convection and radiation loss during heating. The reference thermocouple is pasted directly above this position to ensure that it obtains the highest temperature on the test plate. In this study, the measurement range of the FO-DTS is 2.5 km (±0.5 °C measurement and 0.1 m positioning accuracy), and its spatial resolution is 0.5 m. The refreshing time is set to 3 s.

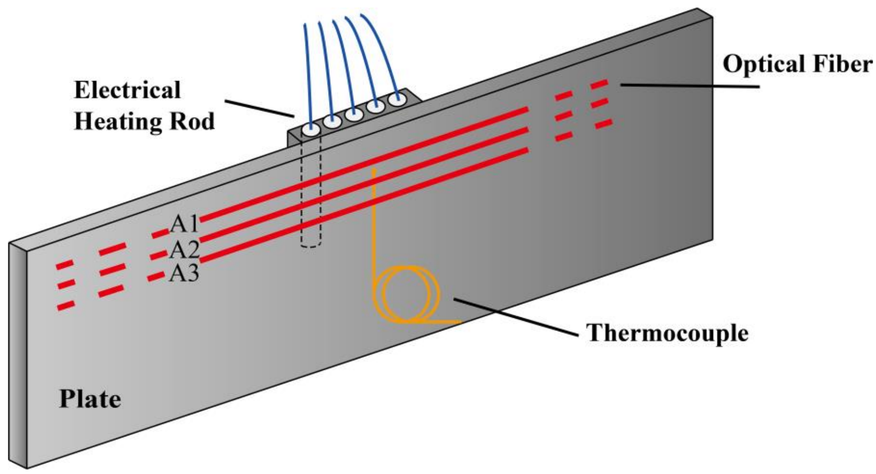

Figure 3. The experimental setup of the exotherm simulation by electrical heating.

3.2. Test Scheme

The combustion process is controlled by the combustibles, combustion environment, and other associated factors, and the temperature variation is complex at different stages of the combustion reaction. The firepower or heat release rate of the fire is always described as constant or variable heat fluxes [31]. In order to fundamentally model the firepower and test the temperature measurement performance of the FO-DTS system under different fire conditions, the experiment adopts a variety of heating powers to provide a diverse exotherm simulation. Moreover, the ability to discover anomalies in an early stage is critical to intelligent fire detection systems, since this can significantly mitigate the losses caused by the spread of the fire. The temperature change on the surface of the test iron plate by electric heating will be limited to a certain low range, which conforms to the scenarios in early-stage fire accidents. The upper boundary of the range is arbitrarily set to 90 °C, and the hot smoke temperature in a fire would definitely be higher than this. The proposed anomaly detection models will be verified in this temperature range to investigate their performance.

To simulate the fire exotherm in the early stage of fire incidents, three representative scenarios are considered in the simulation of exotherm by electrical heating: constant heating power, and continuous heating, with small and large variable heating rates. The detailed steps of the experiment are as follows:

(1) Firstly, the constant heating rate with 5%, 10%, 20%, 30%, 50%, 60%, and 70% of the total electric power is applied to the heating rods, respectively.
(2) Secondly, the large variations in the heating rate over a continuous period of time are investigated. The heating rate of 10%, 25%, and 50% are selected sequentially in this time, each lasting for 150 s.
(3) Finally, the small variations in the heating rate over a continuous period of time are also studied, starting with a 5% heating rate, with an increment of 2.5% every 30 s.

In this experiment, all of the heating terminated after the surface temperature of the iron plate reached 90 °C.

The heating process, with two constant electrical heating rates (10% and 50%) and two patterns of variable rates, produced their responses with different temperature variation trends and peak values when observed using the FO-DTS in this experiment, as shown in Figure 4. The variation trends roughly follow the predesigned heating modes. The returned single temperature data of the FO-DTS is measured by comprehensively considering the Raman backscattering of the stokes and anti-stokes light loss within the spatial resolution (minimum temperature sensing length). The peak values returned from the DTS are slightly different, since the instantaneous heating effect of the iron plate in the spatial resolution range and the consequent regional temperature distribution are distinct in each heating mode. For this unique measurement principle of FO-DTS, rule-based or statistical anomaly detection methods cannot effectively distinguish between normal and abnormal, in most of the applications.

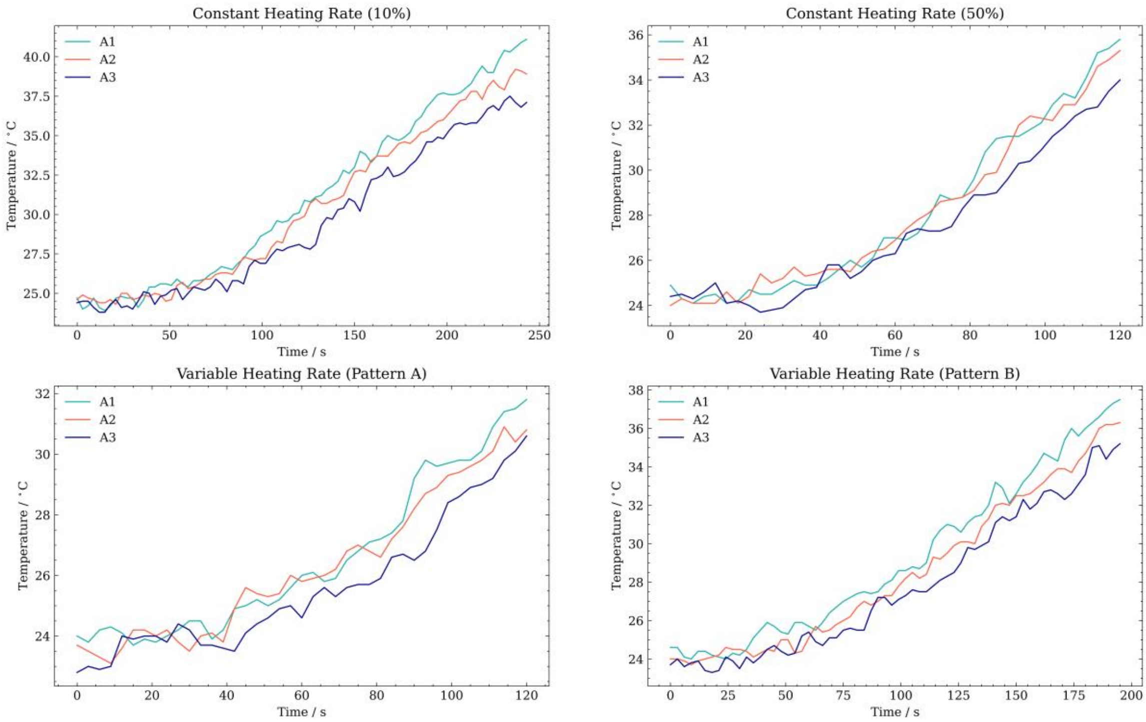

Figure 4. The temperature returned from the optical fibers during the experiment.

4. Results and Discussion

4.1. Anomaly Detection Model Training and Validation

4.1.1. Dataset and Evaluation Metrics

The experiment in the last section generates three groups of standard time series datasets. The sensing data collected from the simulated exotherm with electrical heating are considered as abnormal, and the rest of the temperature data are defined as normal. To create training and test sets, the time window sized 10 was used to slide continuously over the collected temperature data. Finally, the size of the prepared dataset is 16,477 (including 1478 anomalies). The precision, recall, and F1-score are the metrics used to evaluate the performance of the anomaly detection models. All experiments are implemented in Ubuntu LTS 20.04 with PyTorch 1.12.1, CUDA Toolkit 11.6, and cuDNN 8.3 installed.

4.1.2. AE Based Anomaly Detection

Firstly, the AE based anomaly detection model is employed in the evaluation procedure. The normal data is split into training (64%) and validation (16%). In particular, no abnormal data is included in the training and validation sets. The remaining 20% of the normal data and all abnormal data are added to the test set. During the training, the model uses mean squared error (MSE) as the loss function, and Adam as the optimizer [32]. The number of epochs is set to 80, the batch size is 32, and the learning rate is 0.001. In Figure 5, both training and validation sets converge with the iterations, and there is no sign of overfit or underfit. Therefore, the trained AE model can reconstruct the normal signal properly. The parameter q is set to 79 in the AE based anomaly detection to distinguish reconstruction errors between normal and abnormal data.

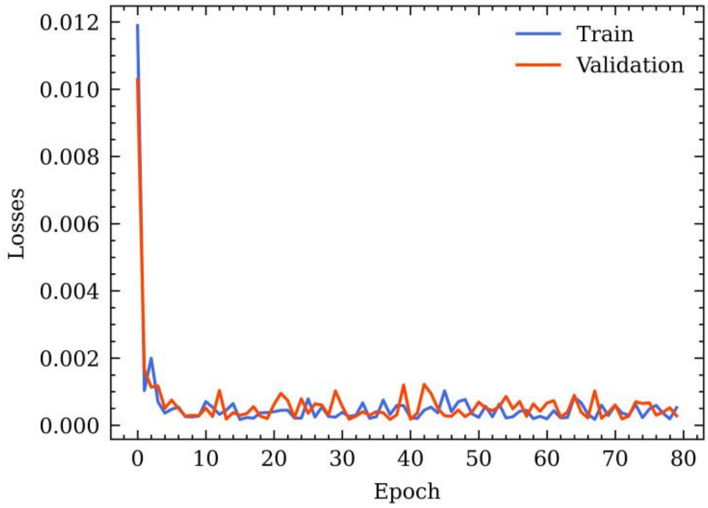

Figure 5. The training and validation losses of the AE model.

The AE based anomaly detection is evaluated in the test set (total size 4478, including 1478 anomalies). The overall accuracy to classify the two categories is 0.81, the anomaly detection precision is 0.90, the recall is 0.65, and the F1-score is 0.75.

4.1.3. CNN Anomaly Detection

For the CNN anomaly detection model, the entire dataset is split into training (65%), validation (15%), and test (25%) sets. During the training, the model used mean squared error (MSE) as the loss function and Adam as the optimizer. The number of epochs is set to 300, the batch size is 16, and the learning rate is 0.001. As shown in Figure 6, with the increase in epochs, the loss decreases and stabilizes at a specific point in both the training and validation sets. The training result indicated that the model is not overfit or underfit.

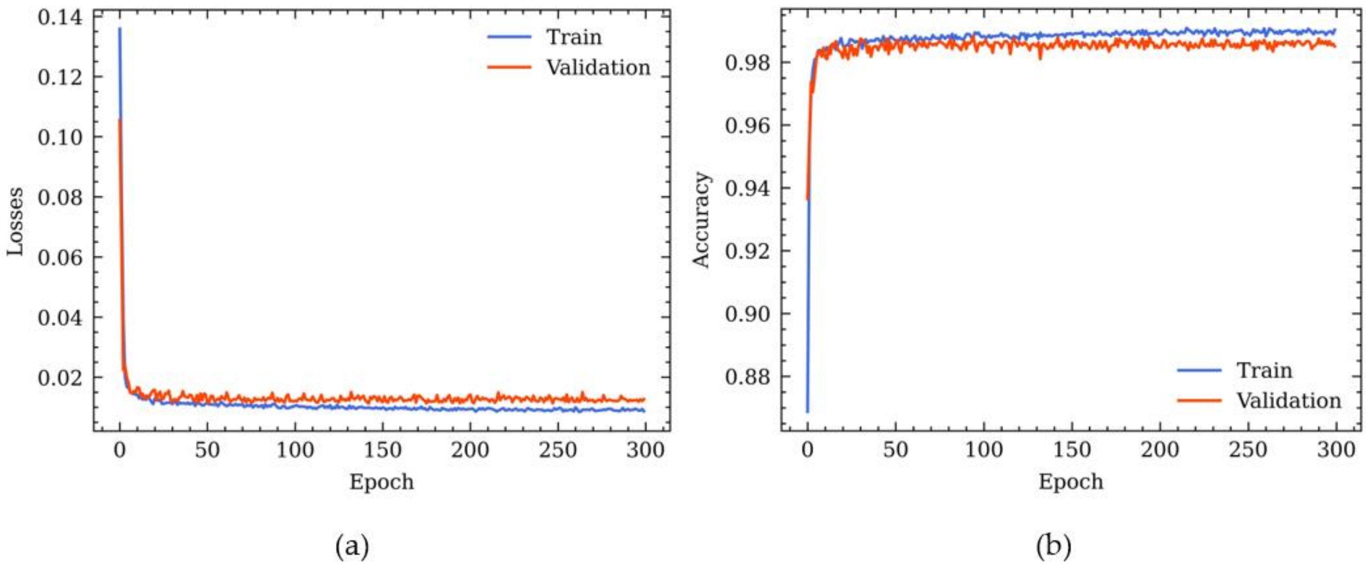

Figure 6. (**a**) The training and validation losses, and (**b**) the training and validation accuracy of the CNN anomaly detection network.

Next, the model is evaluated on a test set with a size of 4120, including 370 anomalies. The overall accuracy to classify the two categories is 0.98. The anomaly detection precision is 0.95, the recall is 0.86, and the F1-score is 0.91.

4.2. Model Performance Comparision

This section presents the performance of the AE based anomaly detection system and the one-dimensional CNN based fire exotherm detection system. From the results demonstrated in Table 3, it is clear that the proposed CNN model has an acceptable performance in monitoring the occurrence of early fire incidents.

Table 3. The performance of the proposed anomaly detection models.

Detection Model	Precision	Recall	F1-Score	Overall Accuracy
AE	0.90	0.65	0.75	0.81
CNN	0.95	0.86	0.91	0.98

The evolution of advanced sensing technology and data-driven anomaly detection methods represented by machine learning have brought about new opportunities for UUT fire detection. In this experiment, the data collected by FO-DTS can accurately reflect the trend of temperature variations according to the simulated electrical heating modes, indicating that it is an effective sensing technology for early fire detection. Meanwhile, the dataset used to train the proposed models was also obtained through the experiment. As an unsupervised learning method, AE does not require labeled data during training, while showing a poor anti-interference ability. The CNN based supervised learning model trained with labeled data has a higher accuracy in the test.

5. Conclusions

The present study was designed to detect the fire exotherm in the early stages of an incident in UUT operations. This research has shown that the FO-DTS have a stable performance in accurately collecting the temperature data during the experiment. This work contributes to existing efforts to implement intelligent fire detection systems in UUT, and it provides a comprehensive assessment of the integration of sensing units and deep anomaly detection algorithms in this application. The results showed that the proposed method has a great potential in overcoming the disadvantages of traditional fire detection techniques. However, the sufficiency and variety of high-quality datasets are the determining factors for the development of data-driven anomaly detection. More efforts are required to further study the simulation of the exotherm patterns in the early stages of UUT fire incidents using the electric heating approach.

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